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Data (R)Evolution – The Economics of Algorithmic Search and Recommender Services

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Abstract: The paper analyses the economics behind algorithmic search and recommender services, based upon personalized user data. Such services play a paramount role for online services such as marketplaces (e.g. Amazon), audio streaming (e.g. Spotify), video streaming (e.g. Netflix, YouTube), app stores, social networks (e.g. Instagram, Tik Tok, Facebook, Twitter) and many more. We start with a systematic analysis of search and recommendation services as a commercial good, highlighting the changes to these services by the systematic use of algorithms. Then we discuss benefits and risk for welfare arising from the widespread employment of algorithmic search and recommendation systems. In doing so, we summarize the existing economics literature and go beyond its insights, including highlighting further research desires. Eventually, we derive regulatory and managerial implications drawing on the current state of academic knowledge.

Keywords: algorithmic search and recommender services, data economics, media economics, internet economics, digital economy, cultural economics, competition, antitrust, industry regulation, digital business ecosystems

JEL-Codes: L86, L40, K21, K23, K24, L13, L51, L82, M21, Z10

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1. Introduction

In recent times, the availability of information (so-called big data) increases the importance of systematic data collection, data processing, data analysis and implementation in various businesses and value chains. The possibility to benefit from data analysis changes (i) industrialized processes (as in artificial intelligence (AI) and machine-to-machine (M2M) communication) and (ii) services based on consumer information. The latter is built on personalized data, i.e. the specific collection of individual information and preferences. It includes both "standard" data (i.e. mail address, name, payment information, gender, etc.), and "advanced" consumer data regarding stated and revealed preferences (e.g. stated: like-button on Instagram; revealed: videos I am actually watching, products I am actually buying) (*Budzinski* & *Kuchinke*, 2020). By combining those two data types and through connecting with data of people with similar behavior and interests so called "derived" data arise which algorithms then altogether can process. Advanced data and sophisticated methods of analysis make it possible to draw conclusions about the consumer's individual consumption habits and discover connections between different behavior- and preference-types over various consumers. People have become accustomed to "paying-with-data"; they provide information to use different services like apps, websites or social media – oftentimes without having to pay monetarily in return.

Three stylized types of business models build on the idea of (consumer) data as payment (*Budzinski* & *Kuchinke*, 2020): (i) user data analysis for third parties, e.g. user-behavior analyses for upstream markets or targeting advertising content on the behalf of companies, (ii) individualized pricing (price discrimination based on data-based estimates of willingness to pay and consumption patterns), (iii) individualized services (tailor-made products and services for consumers). In digital markets, business success is very often rooted in the professional implementation of these individualized services (as in iii). Successful media services like YouTube, Netflix, Spotify, and Instagram but also online shops like Amazon and Zalando benefit from individualized search and recommendation services (SRS) and are in the focus of attention for this article. Think of product recommendations on Amazon based on your previous searching behavior, your top selection on Netflix based on your previous viewing behavior, your personalized playlist "Discover Weekly" on Spotify or profile recommendations on Instagram based on profiles you already follow. The provided consumer data is used for tailor-made search results and recommendations within the platform in order to increase the consumers' consumption (time) which in turn benefits the platform since the more user information is available the better the SRS and algorithms can work (*Belleflamme* & *Peitz*, 2020). The success of these SRS can be seen in the following numbers: according to Netflix already

80 per cent of the content that is watched is based on recommendations (*Morgan*, 2019). Similar and according to Spotify already over 40 million people had turned to the "Discover Weekly" playlist in 2016, not even a year after it had been launched (*Prey*, 2018). For Amazon, *MacKenzie* et al. (2013) revealed already 7 years ago that 35% of the consumer purchases resulted from algorithm-based product recommendations.

Different studies (inter alia: *Accenture*, 2018; *PwC*, 2019; *Deloitte*, 2019) indicate consumers' wish and demand for personalization. Consumers want their personal needs and preferences to be met and accordingly ask for relevant and personalized content, goods, services and/or experience. In that regard algorithmic SRS seem helpful – providing pre-structuring assistance (i.e. rankings and recommendations) to cope with the vast amount of information (information overload) available in the digital world. Other voices, however, speak of gatekeeper effects (*Bozdag*, 2013) or even commercial hypernudging strategies (*Morozovaite*, 2020) going along with (algorithmic) personalization services used by digital platforms.

Taking these quite contrary standpoints, this article aims at providing a differentiated, systematic overview and detailed understanding of algorithmic SRS. Section 2 provides information on types of recommendations, good characteristics and definition of SRS within our research. Section 3 contains the economic discussion, with a literature overview as well as the analysis of positive and negative welfare effects of SRS. Section 4 retrieves both managerial and regulatory implications of the preceding analysis and concludes.

2. Search and Recommendation Services as a Commercial Good

2.1 What are (not) Search and Recommender Services?

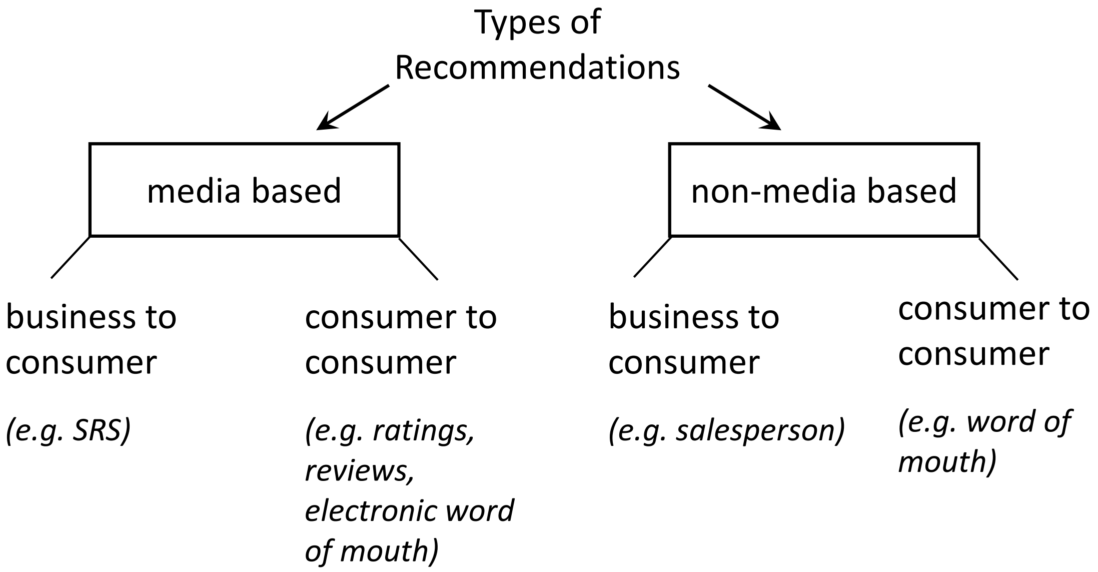
A "good recommendation" is very valuable information, which can be understood as kind advice. The quality of this information can (usually) only be evaluated after consumption (experience good). In specific cases, even after consumption a perfect quality estimation is not possible (credence good) (*Nelson*, 1970; *Wolinsky*, 1995). Generally, SRS can be described as experience goods, since consumers only know the quality of a recommendation after consumption i.e. being definitely (un)satisfied with their choice afterwards. However, if consumers are not sure if the system's suggestions were of good or bad quality, SRS can also have credence good characteristics. This can be the case, for instance, if consumers do quickly rely on recommendations without further research and, hence, not exactly know opportunity costs i.e. what they would have consumed with different recommendations. They have to trust the system and believe in the suitability of the recommendation. Experience and credence goods come with imperfect information; if one market side (either demand or supply side) systematically lacks information, there are information asymmetries (*Akerlof*, 1970; *Budzinski* & *Kuchinke*, 2020). Automatized and algorithmic recommendations are based on (big) data; consumers do not (perfectly) know how recommendations are created. In various cases, consumers are under-informed, which leads to asymmetric information at the expense of consumers. Nevertheless, we consider SRS to be unbiased for the theoretical framework. Incentives for service providers to bias information, search results and recommendations are discussed in Section 3 alongside the welfare effects.

From an economic point of view (a) search and (b) recommendation systems are individualized services and similar, yet not completely the same (*Budzinski* & *Kuchinke*, 2020). (a) Search algorithms are an "answer of the system" regarding active (pull) search actions, e.g. a Google search. The results need to be ranked – including a "recommendation information", since higher placed results are (or seem to be) the better fit regarding the search command (*Edelman*, 2011). Therefore, the ranking in search results is also a recommendation for consumers. Search algorithms usually recommend different alternatives (substitutes). Pure recommender systems (b), without active search command, recommend products or services (push) on a homepage without the consumer actively looking for it, e.g. landing-page or auto-play[1] function on YouTube. The system guides (leads or pushes) the consumer through pages (*Belleflamme* & *Peitz*, 2020), recommending (ostensible) useful content, products and information. While the consumer passively receives recommendations, this can be substitutes (similar alternatives, laptop A or B) or complements (supplementing goods/services, USB stick for laptop A).

Moreover, there are different types of recommendations in the modern world (see Figure 2). Recommendations can be suggested using media technologies (i.e. via some transmitting medium, e.g. digitally with SRS) or non-media based (i.e. directly from person to person). In both cases, they can be differentiated from consumer to consumer (C2C) or business to consumer (B2C).

[1] Many media service providers use auto-play functions, for instance, YouTube plays the next video after the previous one is finished.

Figure 1 Types of Recommendations



Focusing on the media-based side, ratings and reviews are generated through consumers. They are also digital recommendations, for instance, five stars as rating and text reviews for further information on the product on Amazon. Reviews and ratings are C2C recommendations, containing information on "intra-product" level, about the specific good itself, for instance, technical details on laptop A. This means the depth of information on a specific product and its function, durability, features, etc. Their primary role is to reduce information asymmetries between seller and consumer. Reducing transaction cost (e.g. quickly comparing star ratings between laptop A and laptop B) is only a secondary function. SRS are B2C recommendations, providing information on "inter-product" level, comparing, ranking, and recommending different goods within the system. Therefore, mainly reducing transaction costs of searching and deciding between substitutes or finding complementary products, e.g. comparing laptop A and laptop B, suggesting a complementary USB stick. This overview shows that the types of recommendations have different functionality from a theoretical point of view; SRS mainly reduce transaction cost (inter-product), reviews and ratings mainly reduce information asymmetries (intra-product). Additionally, C2C reviews and ratings generate additional data, which can be used as input for SRS.

2.2 Recommendations in the Digital Age

The increasing amount of data and sophisticated analyses in many industries shifted the academic focus towards SRS. With the progress of digitization, SRS gain importance in business models, since advanced methods are necessary to compete for consumers' attention. Yet, SRS are not per se new phenomena of the digital age. Formerly, sellers and shop assistants recommended certain products or services. These recommendations were based on (1) the products in stock and (2) individual needs of consumers. From a theoretical point of view SRS changed in those two dimensions:

(1) Shops had limited resources, regarding the service/product portfolio, for example, lack of space and storage rooms for various alternatives. Online markets are superior in offering niche products, due to aggregate demand without local restraints and different storage/shipping opportunities (see the long-tail theory; *Anderson*, 2004). Moreover, limited human resources, i.e. the sales person played a vital role, knowing the complete product portfolio and comparing goods exclusively for the individual consumer.

(2) The degree of personalization changed with the available amount of consumer data and the means to analyze it (*Belleflamme* & *Peitz*, 2020). Where earlier the trained seller asked for wishes and preferences, algorithmic analysis of masses of consumer data make it possible to compare not only vast amounts of (1) a huge product portfolio, but also give (2) individualized recommendations.[2] Of course, a specific salesperson may know more about a specific (regular) consumer than any algorithmic system may ever do. However, looking at the mass of the cases, algorithms are likely to be superior.

Automatized recommendations, based on detailed, individual information open new quality dimensions. Superior content suggestions, shopping advice, and search results can be produced by these advanced systems. Great business opportunities, but also a lot of innovative pressure, come with sophisticated SRS. Companies, which successfully implement SRS in their business, can profit hugely (historical examples: Google or Amazon). Providing fitting and efficient search results and recommendations can increase sales (i.e. upselling, cross-selling), since consumers quickly find what they need, e.g. on Amazon. To lead consumers skillfully through products and contents can keep them longer on the platform and increase the time they spend, e.g., individualized selection of videos on Netflix or YouTube. Consumers, who like the convenience and quality of recommendations will maximize their time using it and, thus, increase the probability of consuming information, advertising, or other goods. Moreover, the service providers build reputation, since consumers get used to the quality of recommendations, return to the website, or even recommend it to other people (which could

[2] In IT-related literature, three different types of filter systems are typically distinguished for recommendations: (i) *content-based*, based on individual consumer history and similar products, (ii) *collaborative filtering*, based on behavioral patterns of consumers with similar taste and preferences, and (iii) *hybrid recommender system* combination of (i) and (ii) (*Adomavicius* & *Tuzhilin*, 2005; *Gaenssle*, 2021; *Hinz* & *Eckert* 2010; *Zhang* et al., 2019).

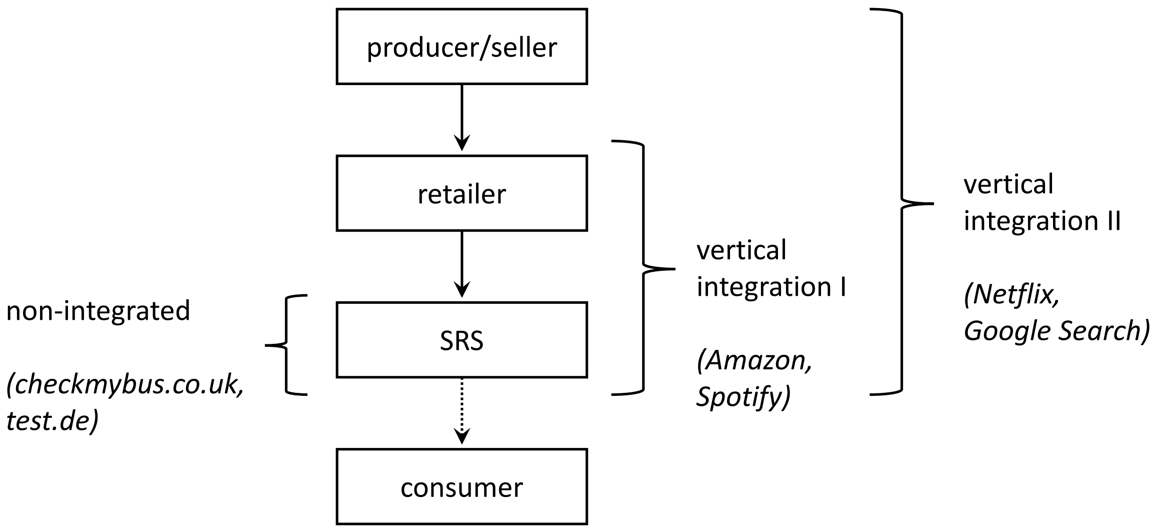
kick-start direct and indirect network effects of modern digital platforms; *Belleflamme* & *Peitz*, 2020). Lastly, the analysis of consumer behavior, their response to the recommendations and different reactions to nudges and suggestions, can be used to further improve the SRS and, moreover, this information can also be part of the data analysis sold to third parties. Hence, the output data of SRS is, again, input for business models (see Introduction; i, ii, iii).

3. Economic Effects of Algorithmic Search and Recommendation Systems

3.1 Literature Review

While there is a more extensive literature on algorithmic search and recommendation systems from an information technology perspective, their treatment within economics has only recently surfaced. Next to more general discussions of the economics behind algorithmic SRS and their role in the digital economy (*Belleflamme* & *Peitz*, 2018, 2020; *Gaenssle* & *Budzinski*, 2020), the question of welfare effects is addressed in a recent series of modeling papers. They do not discuss isolated, non-integrated SRS (see Figure 2, SRS Vertical Integration). Instead, 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* et al., 2020). *Hagiu* et al. (2020) add an outside option for the upstream goods' providers (direct sale). *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 streaming services, *Hagiu* et al. (2020) on marketplace services and *Padilla* et al. (2020) on app store services.

Figure 2 SRS – Vertical Integration



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* et al., 2020; *Padilla* et al., 2020). This bias is usually profitable for the vertically-integrated company but harmful for consumer and social welfare (*Drugov* & *Jeon*, 2018; *Hagiu* et al., 2020; *Padilla* et al., 2020). Only *De Cornière* and *Taylor* (2020) identify a case for non-harmful bias. They distinguish between "conflict" and "congruence" between the pay-offs 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.

Even though 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, it informs our analysis of welfare effects and regulatory implication in the next sections. Notwithstanding, we go beyond the pure modeling literature.

3.2 Positive Welfare Effects

Using algorithmic SRS is beneficial and profitable for the companies (*Budzinski* & *Kuchinke,* 2020). By providing individualized search rankings and recommendation services and thus (better) meeting the consumers’ individual preferences, companies can intensify the users’ transactions and consumption time with the respective service which in turn increases demand and turnover. According to *Fleder* and *Hosanagar* (2009), recommender systems can be beneficial in three ways: turning browsing consumers into buyers, cross-selling as well as increasing customer loyalty. Moreover, algorithmic SRS may also be used as a promotional tool for other goods offered by the same company. Profits are then derived from higher sales and uses of the upstream goods offered by the respective company. The longer and more extended the users spend time with a specific service provider the more personalized data (again) will be available to gather from the company. This includes learning from the reactions of the consumers on the actual suggestions of the SRS and further improving the algorithms. This additionally gained data can then again be profitably used by the companies for:

- further improvements of the individualized SRS, generating a self-reinforcing mechanism.
- vertical or horizontal integrated services of the company. Netflix and Amazon, for instance, take advantage of user data from its streaming services that increase the competitiveness of their own-productions of audiovisual content because they can better estimate what viewers probably like (*Gaenssle,* 2021). Facebook serves as a horizontal example by using personalized data from WhatsApp in order to optimize their Instagram service. Profitability then originates from improving related goods and increasing their usage and/or sales.

- third-parties who are willing to pay for the analysis of the data or its results, respectively. Spotify, for instance, makes money by selling data analyses (the analysis result, not the data itself) upstream to the music industry. Another example presents targeted advertising. In that case, online services sell the result of their data analysis to advertisers by placing their ads particularly to those consumers who, according to data-based estimations, are the most probable ones to purchase the advertised goods.
- data-based price discrimination. Here a company operates with its user data to estimate the willingness-to-pay of individual consumers to adjust prices accordingly. Reaping consumers' rents by individualized pricing is obviously highly profitable for the companies.

Also, consumers benefit from algorithmic SRS causing positive effects on consumer welfare. In general, transaction costs can be reduced (see section 2). More precisely, search costs for the consumers are reduced (*Hinz* & *Eckert*, 2010; *Brynjolfsson* et al., 2011; *Belleflamme* & *Peitz*, 2018, 2020; *Budzinski* & *Kuchinke*, 2020). On the one hand, the internet itself reduces search costs compared to traditional offline markets (inter alia *Ghose* & *Gu*, 2006; *Hinz* & *Eckert*, 2010). On the other hand, digital markets are able to offer a much larger amount of goods compared to traditional brick and mortar stores which in turn considerably increases the amount of information available (information overload problems). This can be owed to the following reasons: i) storage costs are oftentimes significantly lower online which is even more the case if goods can be stored digitally, such as streaming services, ii) costs of geography decrease in the digital world. This allows for offering niche products that meet the consumers' demand for goods which would be too dispersed for local stores to offer/store the good. Online, however, the so-called long-tail effect applies (inter alia, *Anderson*, 2004; *Brynjolfsson* et al., 2011) – the accumulation of demand for niche products makes the selling of these goods profitable. The vast amount of available goods and information, however, can cause information overload problems. Thus, search and recommendation tools seem to be highly important (*Brynjolfsson* et al. 2006) as they can offer pre-structuring assistance letting the consumers find more quickly what they are searching for. Due to the preference-oriented ranking of search results, consumers benefit from a better overview on relevant offers (increasing market transparency).

In addition to this, recommendations can provide decision support (*Milano* et al., 2020; *Lee* & *Hosanagar*, 2015). Through providing recommendations that match the users' preferences decision costs can be reduced. The previously mentioned huge amount of available goods online compared to offline creates the so-called abundance-of-choice problem for users (information overload). This in turn demands for external recommendations, with algorithmic recommendations being more suitable to cope with the vast amount of (big) data. According to *Fleder* and *Hosanagar* (2009), recommender systems can benefit the consumers by getting them aware of new products as well as facilitating product selection among the endless options available. *Jannach* et al. (2017) point at two additional aspects how recommender systems might positively influence consumers: i) by acting as reminders for products that the user had a prior interest for, ii) by pointing the attention to products that are currently price reduced. The effectiveness of algorithmic recommendations can be drawn from different empirical studies confirming 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). Also, *Senecal* and *Nantel* (2004) found in their empirical research that recommender systems were the most influential recommendation source among different types of online recommendation sources (e.g. other consumers, human experts).[3]

The improved market overview through algorithmic SRS also facilitates one-stop shopping behavior for the consumers online. This in turn could provide different advantages for the consumer compared to various single shopping activities at different shopping venues: i.e. less shopping costs (i.e. saving multiple delivery/shipping costs), time savings (focusing on one online shop instead of browsing multiple shops), convenience aspects (log-in data for only one shopping venue), privacy aspects (providing personal data to just one or a few number of online shops) as well as again a further reduction in search and decision costs (see above).

The benefits are particularly high for consumers who have a high adversity against search and decision costs and least relevant for consumers who enjoy the search and decision process. Transferring the insights from behavioral economics about rule-following behavior (inter alia, *Vanberg*, 1994, 2002; *Budzinski*, 2003) to the digital age, consumers should particularly benefit from algorithmic SRS in the case of low-key and routine consumption decisions than in the case of exceptional and outstanding important transactions. A good fit of the SRS' data-based estimations with the preferences for routine consumption (which is often conducted satisfycing utility instead of maximizing utility) allow for a minimization of transaction costs (as search and decision costs). This is beneficial because it saves cognitive resources for non-routine decisions where the consumption act is of paramount importance for the consumer.

[3] Though regarding trustworthiness and expertise the recommender system performed not as good as other users and human experts (*Senecal* & *Nantel*, 2004).

Here, the SRS results are more likely to be critically reviewed and complemented by additional information, for instance from reviews and ratings or experts. Taking a Spotify-style streaming service as an example, an individual is likely to more or less blindly follow playlist recommendations when she comes from everyday work and just wants to relax a bit than in the case of a first rendezvous with a new love where the individual probably will want to make sure the right music is played and not "only something".

However, not only the preferences of consumers are heterogeneous but also their sensitivity towards algorithmic SRS differs. The spectrum may encompass extreme positions: a general distrust and skepticism towards algorithmic SRS (strong preference for self-determination) on the one end, leading to rejecting SRS suggestions as a matter of principle, and, on the other end, the notion that the algorithmic SRS anyhow knows better what I want than myself (Baumgartl-effect), resulting in a rather blind following of top ranked SRS results. In economic terms, the recommendation-elasticity of demand differs among individuals, based upon relevance of search and decision costs as well as personal attitude towards algorithmic SRS. Benefits of SRS – but also negative effects – considerably depend on the individual shape of this recommendation elasticity.

3.3 Negative Welfare Effects

3.3.1 Consumption Bubble

The creation of automatized algorithmic recommendations based on individualized preferences can lead consumers into a specific direction and create path dependency. The consumer information is analyzed by the system that generates suitable recommendations. SRS consequently influence which content is displayed to recipients and either presented on top of search lists or remain hidden i.e. listed among the last results (*Bozdag*, 2013). Iterative feedback loops lead to learning processes and suggestions according to the consumer's (first and subsequent) interests. This can fuel the development of so-called filter bubbles and echo chambers.[4] Since these terms are mainly used for news consumption, we refer to this more generally, as consumption bubbles. Stuck in a consumption bubble, consumers only receive recommendations closely related to their main interests and do not get confronted with new, surprising contents anymore, which reduces diversity. The great advantage of SRS, reducing

[4] There is a broad literature on media bias and filter bubbles in news markets (inter alia, *Borgesius Zuiderveen* et al., 2016; *Del Vicario* et al., 2016; *Flaxman* et al. 2016; *Jamieson* & *Cappella*, 2010; *Sunstein*, 2009, 2017).

transaction cost and information overload, can subsequently become a disadvantage and welfare reducing.

There are different factors, which influence the development of consumption bubbles. The more points are fulfilled (and the stronger in itself), the higher is the probability of a consumption bubble.

- Homogeneous preferences for the recommended good: SRS recommend according to the individual consumer's preferences. If they are very homogeneous regarding the recommended good, there is no need to provide further or other information. The system's suggestions will usually vary among the same good/service types without large variance.
- The presence of naïve consumers (*Heidhues* & *Köszegi*, 2017): Consumers who are not skeptical towards SRS and simply rely on recommendations without further research or critical consideration (see section 3.2). The probability to get stuck in a consumption bubble increases with naiveté, as there is no critical examination of outside opportunities. Moreover, there is empirical evidence that the majority of consumers is not aware of pre-selection and algorithmic filtering (in social media; *Rader* & *Gray*, 2015).
- Simplicity of one-stop shopping: It is very convenient to receive all goods and services in one place. Transaction costs of information sharing (giving personal data, payment data etc.) are lower. Consequently, the consumer relies on the recommendation of one shop, without checking outside options.
- Building consumption capital (*Stigler* & *Becker*, 1977; *Adler*, 1985): Consumers collect specific knowledge on two dimensions (i) the system they are using, (ii) the goods/services they are consuming. On level (i) consumers get to know the service and its SRS; they know how to use the system, where to klick, what recommendations they like and use, e.g. knowing how to filter Amazon shopping lists. On (ii) they get to know specific offers and products (especially for reoccurring or serial consumption), e.g. Netflix Originals. This way, consumers can build taste and knowledge in a specific direction (*Stigler* & *Becker*, 1977).

From a normative perspective, the individual consumer might be happy in a comfortable consumption bubble, without (irrelevant) outside information, which could increase decision costs or cognitive dissonance. Yet, this path-dependency might not always be welfare enhancing; only an experienced consumer with settled and well-established preferences, who exactly knows what she likes, is sure that she does not miss something. The consumer builds consumption capital in one direction, but there is no creation of taste etc. in another direction. Therefore, she misses opportunities, learning processes and taste-building chances.

Moreover, from a collective point of view on society, consumption bubbles might lead to problems on a bigger scale and in the long run. On the one hand, the segregation of various small bubbles can reduce social cohesion, mutual understanding and collective development/innovation. In media sectors,[5] the co-existence of various small but segregated bubbles can weaken the cultural identity, which can be important for solidarity and social cohesion, for instance, loss of nation-wide music hits that everybody knows due to individual streaming bubbles. However, critical voices find no empirical evidence of those effects so far (*Borgesius Zuiderveen* et al., 2016; *Gentzkow* & *Shapiro,* 2011; *Pogorelskiy* & *Shum,* 2019). On the other hand, the creation of one major bubble can lead to loss of diversity and individuality. All consumers build the same consumption capital and collective knowledge is minimized to the same standards (race-to-the-bottom). The individual knowledge does not differ, thus, the dependency on a specific system can increase, for example, depending on specific knowledge on Apple/Windows systems. The specific knowledge increases switching costs, which can strengthen market power positions (with all incentives of abuse) in the long run.

3.3.2 Scale Effects and Monopolization

One of the marked differences between the recommending salesperson in a physical shop and an algorithmic SRS implemented by an online service relates to the resulting market structure. In stark contrast to the more decentralized classic recommendation competence of human experts (scattered across millions of shops, organizations, etc.), algorithmic SRS represent a strong centralization of recommendation knowledge. Based upon big data input, one big algorithm (or one system of integrated algorithms) produces individualized search rankings and recommendations. Furthermore, the fundamental centralization of knowledge is accompanied by the dependence of the quality of search and recommendation results on the amount of data input: more data input leads to better estimations of consumer's preferences and, thus, to better SRS performance. Scale effects advantage big SRS suppliers over smaller ones and create barriers to entry for newcomers. This favors a market structure with either a narrow oligopoly

[5] More severe effects can be found in news markets, with implications for democratic values and political decisions (see *Borgesius Zuiderveen* et al., 2016). This important research field is, however, not the main focus of this paper.

of few big global players or even one leading supplier enjoying a dominant position. Without any countervailing effects, even a monopoly would be feasible for the SRS market.

However, there are some countervailing factors. First, the law of diminishing marginal returns also holds true for algorithmic SRS: while more data is always useful, the additional advantage of more data decreases beyond a certain threshold. Thus, the quality differences among suppliers all working with big data amounts becomes negligible and hardly recognizable for imperfectly informed, behavioral consumers. Second, personalized data, which is the resource feeding the algorithms, is non-rival in character and can be reproduced by the consumers. Hence, it is not exclusive to one SRS. Consumers can reveal their personal data to many services without exhaustion of the good “personal data” and many online services can parallel track the same consumer and her browsing and consumption behavior. Consequently, the data feeding the algorithms is non-exclusive and every smaller SRS supplier or newcomer can amass the necessary data to become competitive with the incumbents. This does require some investment so that the SRS market is not perfectly contestable. However, this is hardly different from other markets. Third, technological switching costs between SRS are low, so that competing services can attract users on the merit.[6]

Altogether, it appears to be unlikely that algorithmic SRS lead to a monopoly. However, providers of algorithmic SRS enjoy more market power than traditional SRS do.

3.3.3 Bias

If providers of SRS experience incentives to bias the ranking of search results and recommendations, consumer welfare may be jeopardized in favor of the profits of the SRS providers. *A priori*, biasing SRS should be negative for SRS profits because maximizing the fit with individual consumer preferences is profitable and deviating from this may drive consumers away from using the service (see section 3.2). As such, algorithmic SRS c.p. enhance consumer welfare. Notwithstanding this general insight, SRS providers may experience scope for profitable bias under certain circumstances (see also section 3.1). This scope differs between non-integrated and vertically integrated SRS providers – and amongst the latter the type of vertical integration matters as well (see Section 3.1, Figure 2, SRS Vertical Integration).

For non-integrated SRS providers, biases can be profitable if the SRS provider benefits from consumers choosing *specific* goods from the search results and recommendations over *others*.

[6] Path dependencies based upon consumer behavior are discussed in the context of consumption bubbles (see above).

Assume the provider of a SRS earns different margins depending on which goods the consumer chooses from the search and recommendation lists. Examples include comparison services where upstream suppliers pay for each consumer directed to them through this comparison website (pay-per-click) or search engine services. Then, the SRS provider experiences incentives to recommend preferably goods where its profit margin is highest as well as to rank these items systematically higher in search results, independent of the estimated consumer's preference. Obviously, this incentive is even stronger when upstream suppliers directly pay for better SRS rankings.

The case of vertical integration I (see Figure 2) is similar but increases incentives to bias because more variables influences profit margins, so that they are more likely to differ between upstream good suppliers. For instance, streaming services are likely to negotiate different royalties with different upstream content providers and marketplace services are likely to draw differing retail margins from different upstream goods. They then experience incentives to rank the contents and goods with the higher profit margin systematically higher. While such a bias is profitable, it reduces consumer welfare and, in total, harms social welfare (*Bourreau* & *Gaudin*, 2018). The scope for bias is limited by the intensity of competition (*Bourreau* & *Gaudin*, 2018; *De Cornière* & *Taylor*, 2020; *Hagiu* et al., 2020) and the sensitivity of consumers to biased recommendations (*Bourreau* & *Gaudin*, 2018; *De Cornière* & *Taylor*, 2020).

Vertical integration II (see Figure 2) generates an additional incentive for harmful algorithmic search and recommendation bias, namely the so-called self-preferencing. If the SRS provider is vertically integrated to the extent that some of the goods ranked in his search and recommendation lists are from the same company or the same group of companies, then biasing the results in favor of these goods can even be profitable if it drives some consumers away. As long as the additional sales of the upstream goods offset the marginal losses of SRS usage, an integrated company finds it profitable to bias its SRS. For instance, the *European Commission* (2017) found in its GoogleShopping case that Alphabet-Google deliberately biased its GoogleSearch service in order to steer the traffic towards GoogleShopping and away from competing comparison services. According to the *European Commission* (2017), this was done by implementing a penalty points system into the algorithm, which downgraded the ranking of specific competitors of GoogleShopping in the search rankings, so that they disappeared from the first page of search results. The strategy was successful as it significantly changed the market shares of online comparison services in favor of GoogleShopping and at the expense of its competitors, but it harmed social welfare (*European Commission*, 2017). According to the state of research (see section 3.1), the probability of harmful self-preferencing increases with the following characteristics:

- higher market power in the SRS market.
- higher market power in the retailing market with which the SRS is integrated (*Bourreau* & *Gaudin*, 2018; *De Cornière* & *Taylor*, 2020; *Hagiu* et al., 2020).
- higher market shares (even below traditional market power thresholds but of course also beyond those) of the integrated firm 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 SRS (*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).
- 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 SRS plays only a minor role if the SRS 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 depends on considerable market power, severely limiting alternatives to the dominant SRS for consumers. Effective competition erodes the incentives for biases. Things look different if vertical integration extends to upstream levels which provide/sell the goods that get ranked by the SRS (vertical integration II in Figure 2). This represents the problematic case where harmful bias in the form of self-preferencing must be expected to prevail.

3.3.4 Privacy

Whenever personalized data is collected, processed, and commercially analyzed, issues of privacy play a relevant role. Obviously, privacy is a multi-disciplinary issue. However, in the context of our analysis, privacy matters with respect to its effects on welfare. The economics of privacy (overview: *Acquisti* et al., 2016) analyze under which conditions market players (including consumers) make welfare-optimal decisions regarding the revelation or disguise of personal data. The modern literature that focuses on online markets emphasizes information asymmetries at the expense of consumers: if consumers cannot know for what and by whom their data is commercially used, they cannot make a rational decision about its provision and inefficiencies occur (inter alia, *Taylor*, 2004; *Acquisti* & *Varian*, 2005; *Hermalin* & *Katz*, 2006). Similarly, a lack of competition, i.e. a lack of alternatives for consumers to choose between, causes welfare harm (*Kerber*, 2016). Personal data may be overprovided compared to the aspired level of privacy and the commercial value of data may be undervalued (*Budzinski* & *Kuchinke*, 2020).

Consumers can get a relatively proper idea that their data is used to rank search results and provide individualized recommendations when using a service with an algorithmic SRS. Usually, they will not know how the algorithm exactly works but in the absence of hidden bias (see above) and the presence of effective competition this should be no problem as they can assess whether the recommendations match their preferences or not. However, if the SRS provider processes or sells the personalized data to third parties for further commercial purposes, it becomes less likely that the consumer can anticipate the commercial use and value of its data provision. This is further fueled by the common phenomenon that consumers largely ignore available information about data usage and privacy conditions provided by service providers in their general terms and conditions (*Obar* & *Oeldorf-Hirsch*, 2018). The Cambridge Analytica case provides an example where most consumers were not aware of a third-party use of their data (although perhaps based more on political than commercial purposes) as does the German antitrust case against Facebook's non-transparent data extraction through third parties (inter alia, *Budzinski*, *Grusevaja* & *Noskova*, 2020). Note, however, that this privacy issue does not apply if an SRS provider sells the results of its *data analysis* and does not trade the data itself. Spotify's business of selling streaming data analysis to the upstream music industry represents such an example.

4. Implications and Conclusion

4.1 Managerial Implications

SRS present efficient and helpful tools for digital operating companies (e.g. online shops, (social) media services) by providing consumers with pre-structuring assistance for dealing with the vast amount of products, services and information available, thus, facilitating purchasing and/or consumption decisions (i.e. reducing transaction costs). Consumers value such form of personalized recommendation, with many consumers tending to click on the top ranked search and recommendation results. Also, different companies (e.g. Amazon, Netflix) reveal that a considerable percentage of consumption is already based on recommendation systems (see section 1). SRS have the potential to increase profits – i.e. generating cross- and up-selling opportunities by making their customers aware of new products, price reduced products that otherwise probably would not be purchased, niche products that meet the individual demands of their customers (in line with the long-tail effect) as well as reminding them of products they had a previous interest in (see section 3.2). The better the algorithmic SRS meet the personal needs of the individual consumers the more time and/or money they will spent with the respective service. By doing so, reputation can be built, leading to customer loyalty (consumers put trust in the companies' recommendation), one-stop shopping behavior by satisfied consumers and/or positively influencing C2C recommendations ((digital) word of mouth effects, e.g. recommending the service/shop to a friend who becomes a new customer). Companies should therefore continuously analyze (consumer) data as well as evaluate the success of the given SRS (i.e. was the recommendation actually used by the consumers and led to further purchases and/or consumption) in order to further improve the algorithms. Thus, the availability and thorough analysis of (big) data (i.e. basic, advanced and derived consumer data), plays a crucial role for the functioning and enhancement of the SRS.[7] In addition to this, further business models, such as the use of third-party services (e.g. targeted advertising), vertical or horizontal integrated services as well as individualized pricing can be positively influenced.

Last but not least, this article has elaborated a distinction of different forms of recommendations, going along with different functionalities (e.g. B2C vs. C2C recommendations). Companies should be aware of these differences, trying to combine different recommendation types in order to positively influence consumers' consumption and/or purchasing decisions. For instance, whereas for routine consumption SRS might suffice more important transactions

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[7] At the same time, however, companies should be aware of possible privacy concerns by the consumers in revealing (too much) personal data.

should be actively accompanied with the promotion of C2C recommendations such as ratings and reviews in order to strengthen credibility in the respective algorithmic recommendation and reduce information asymmetries.[8] By doing so, also possible privacy concerns of the consumers could be reduced.

Since algorithm-based SRS increasingly come under scrutiny of regulatory authorities and governments (see section 1), companies employing such SRS should safeguard that they comply without antitrust and consumer protection laws. This particularly refers to incentives to bias search rankings and recommendations. While such biasing strategies may be profitable in the short run, they fuel the tightening of competition rules and promote public regulation of algorithmic SRS. Especially the latter entails the danger of far-reaching interventions into business models and commercial opportunities as well as into managerial freedom. Withstanding incentives to self-preferencing – as profitable as that may be in the short-run – represents an important element to prevent far-reaching government intervention into this market.

4.2 Regulatory Implications

Regulatory implications need to highlight the beneficial character and consumer-welfare enhancing elements of algorithmic SRS. Any regulatory intervention should aim to preserve the comprehensive advantages and pinpoint combating welfare-decreasing practices. Even though research on this comparatively new service, which is still dynamically developing, is ongoing, the state-of-the-art already offers a number of valuable insights. First, negative welfare effects are likely to surface in specific market constellations. Consequently, a general industry-wide sector regulation of SRS represents an inadequate regulatory tool since it does not pinpoint the problematic cases but imposes a one-size-fits-all regulation upon everything including the welfare-enhancing cases. This would create a number of negative side-effects like slowing down of innovation, eroding incentives to service improvements, burdening significant regulatory costs on business and taxpayers (also through a dynamically self-reinforcing enforcement bureaucracy), and entailing the danger of initiating an intervention spiral. This is particularly dangerous if regulatory authorities try to regulate what consumers should receive as search rankings and recommendations – for instance, in order to break-up consumption bubbles or prevent biased SRS. Due to unavoidable imperfect regulatory knowledge and self-interests of regulatory authorities, consumers are likely to become restricted in their freedom of choice and end up with even more welfare losses in such scenarios.

[8] Additionally, such data can again be incorporated in the algorithm of the SRS.

Since the profitable employment of welfare-harming biases of search rankings and distorted recommendations considerably depends on market power and vertical integration, especially of type II (see figure 2 and sections 3.3.2 and 3.3.3), competition policy represents an adequate tool to effectively and precisely address welfare-reducing business strategies. In contrast to sector regulation, competition authorities executing antitrust law only intervene into cases, where negative consumer welfare effects actually occur – and stay away from all other cases, thus, leaving innovation incentives as well as business and consumer freedom more intact. In doing so, competition policy may use a wide range of instruments, depending on the respective laws in each jurisdiction. The strongest intervention would be to break-up powerful companies in several smaller entities, for instance in order to reduce horizontal market power or to end vertical integration. The dual role problem of the same company acting as a SRS service and as an upstream seller of recommended goods, which generates considerable and problematic self-preferencing incentives could be effectively solved by breaking-up such companies and create mutually independent firms on the different supply-chain stages. Such an intervention may increase social welfare if price competition is more relevant in a given market than quality/utility competition (*De Cornière* & *Taylor*, 2020). Otherwise, however, breaking-up the integrated firm may decrease social welfare because of a reduction both in innovation dynamics and service quality for the consumer (*Hagiu* et al., 2020). However, a general prohibition of self-preferencing always increases consumer welfare (*De Cornière* & *Taylor*, 2020; *Hagiu* et al., 2020) and if self-preferencing is combined with market power, i.e. upstream competitors are dependent on the integrated company, also total welfare (*Hagiu* et al., 2020). While prohibiting self-preferencing implies to intervene against a specific practice in a specific market, the more general introduction of a neutrality obligation requiring a randomized order of search and recommendation rankings reduces welfare because it softens competition between the upstream goods/content providers (*De Cornière* & *Taylor*, 2020), thus eroding the procompetitive effect of algorithmic search and recommendation systems. Enforcing 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).

Thus, empowering competition policy to combat self-preferencing represents the preferable regulatory avenue. In most jurisdictions, the current laws should allow for intervening against harmful self-preferencing of dominant companies as it constitutes an abuse of dominance. Still, it requires to go beyond the predominant antitrust philosophy of focusing on horizontal practices and re-activate both the critical view on vertical (and conglomerate) effects

(*Budzinski* & *Stöhr*, 2019) and the enforcement against exclusionary abuses (*Bougette* et al., 2019). However, the application of traditional market power concepts is limited in digital markets and harmful may also appear below the thresholds of market dominance. Therefore, an enhancement of the tools of competition authorities is necessary to effectively combat anti-competitive SRS-strategies. The extension of the antitrust market power concepts to embrace systemic market power in digital ecosystems represents a promising way forward (*Budzinski*, *Gaenssle* & *Stöhr*, 2020). In Germany, the currently ongoing reform of competition rules includes the introduction of a position of "outstanding relevance across markets" (ORAM), which seeks to cover systemic market power in digital ecosystems. A consequence of identifying such a position would then be to prohibit certain business behaviors including, inter alia, self-preferencing. Similar ideas are discussed on the European level although, here, also the idea of a comprehensive sector regulation covering also algorithmic SRS is not yet off the agenda.

References

Accenture (2018). Making it Personal. Why brands must move from communication to conversation for greater personalization. Pulse Check 2018. Accenture Interactive. Available at: https://www.accenture.com/_acnmedia/pdf-83/accenture-making-personal.pdf (Accessed: 6 November 2020).

Acquisti, A., Taylor, C.R. and Wagman, L. (2016). The Economics of Privacy. *Journal of Economic Literature*, 54(2), pp. 442-492.

Acquisti, A. & Varian, H. R. (2005). Conditioning Prices on Purchase History. *Marketing Science*, 24(3), pp. 367–381.

Adler, M. (1985). Stardom and Talent. *The American Economic Review*, 75(1), pp. 208-212.

Adomavicius, G. & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, 17(6), pp. 734-749.

Aguiar, L. & Waldfogel, J. (2018). Platforms, Promotion, and Product Discovery: Evidence from Spotify Playlists. NBER Working Paper 24713.

Akerlof, George A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism, *The Quarterly Journal of Economics*, 84(3), pp. 488-500.

Anderson, C. (2004). 'The Long Tail'. Wired Magazine, 01 October. Available at: https://www.wired.com/2004/10/tail/ (Accessed: 28 October 2020).

Belleflamme, P. & Peitz, M. (2018). Inside the Engine Room of Digital Platforms: Reviews, Ratings and Recommendations, in: J. J. Ganuza & G. Llobet (eds), Economic Ananalysis of the Digital Revolution. Madrid: Funcas.

Belleflamme, P. & Peitz, M. (2020). Ratings, Reviews, Recommendations and the Consumption of Cultural Goods. In: Ruth Towse and Navarrete Hernández, eds., *Handbook of Cultural Economics*, 3rd ed. Cheltenham: Edward Elgar Publishing, pp.466-473.

Borgesius Zuiderveen, F. J.; Trilling, D.; Möller, J.; Bodó, B.; De Vreese, C. H. & Helberger, N. (2016), Should we worry about filter bubbles? *Internet Policy Review*, 5(1), pp. 1-16.

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

Bourreau, M. & Gaudin, G. (2018). Streaming Platform and Strategic Recommendation Bias, Available at: https://ssrn.com/abstract=3290617 (Accessed: 28 October 2020).

Bozdag, E. (2013). Bias in algorithmic filtering and personalization. *Ethics Information Technology*, 15(3), pp. 209-227.

Bruns, A. (2019). Filter bubble. *Internet Policy Review*, 8(4), pp. 1-14.

Brynjolfsson, E, Hu, Y, Smith, M. D. (2006). From Niches to Riches: The Anatomy of the Long Tail. *Sloan Management Review*, 47(4), pp. 67-71.

Brynjolfsson, E., Hu, Y., Simester, D. (2011). Goodbye Pareto Principle, Hello Long Tail: The Effect of Search Costs on the Concentration of Product Sales. *Management Science*, 57(8), pp. 1373-1386.

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

Budzinski, O., Grusevaja, M. and Noskova, V. (2020). The Economics of the German Investigation of Facebook's Data Collection. *Ilmenau Economics Discussion Papers*, 26(139), pp. 1-37.

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.

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

Budzinski, O. & Stöhr, A. (2019). Competition Policy Reform in Europe and Germany - Institutional Change in the Light of Digitization. *European Competition Journal*, 15(1), pp. 15-54.

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

Deloitte (2019). The Deloitte Consumer Review. Made-to-order. The rise of mass-personalisation. Deloitte. Available at: https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/consumer-business/ch-en-consumer-business-made-to-order-consumer-review.pdf (Accessed: 6 November 2020).

Del Vicario, M.; Vivaldo, G.; Bessi, A.; Zollo, F.; Scala, A.; Caldarelli, G. & Quattrociocchi, W. (2016). Echo Chambers: Emotional Contagion and Group Polarization on Facebook, *Scientific Reports*, 6 (37825), pp. 1-12.

Drugov, M. & Jeon, D.-S. (2017). Vertical Integration and Algorithm Bias, Conference Paper, Available at: https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=IIOC2019&paper_id=431 (Accessed: 28 October 2020).

Edelman, B. (2011). Bias in Search Results?: Diagnosis and Response, *The Indian Journal of Law and Technology*, 7, pp. 16-32.

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

Flaxman, S.; Goel, S.; Rao & J. M. (2016). Filter Bubbles, Echo Chambers, and Online News Consumption. *Public Opinion Quarterly*, 80(S1), pp. 298-320.

Fleder, D. & Hosanagar, K. (2009). Blockbuster Culture's Next Rise or Fall: The Impact of Recommender Systems on Sales Diversity. *Management Science*, 55(5), pp. 697-712.

Gaenssle, S. (2021). Big Data Comes to Hollywood – Audiovisuelle Medienmärkte im Digitalen Zeitalter, in: O. Budzinski, J. Haucap, A. Stöhr & D. Wentzel (Hrsg.), *Zur Ökonomik von Sport, Entertainment und Medien – Schnittstellen und Hintergründe*, Berlin: DeGruyter, forthcoming.

Gaenssle, S. & Budzinski, O. (2020). Stars in Social Media: New Light Through Old Windows?, *Journal of Media Business Studies*, (published online 04 April 2020).

Gentzkow, M. A. & Shapiro, J. M. (2011). Ideological Segregation Online and Offline. *The Quarterly Journal of Economics*, 126 (4), pp. 1799–1839.

Ghose, A. & Gu, B. (2006). Search Costs, Demand Structure and Long Tail in Electronic Markets: Theory and Evidence. NET Institute Working Paper No. 06-19.

Ghose, A. & Yang, S. (2009). An Empirical Analysis of Search Engine Advertising: Sponsored Search in Electronic Markets. *Management Science*, 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.

Hermalin, B. E. and Katz, M. L. (2006). Privacy, Property Rights and Efficiency: The Economics of Privacy as Secrecy. *Quantitative Marketing and Economics*, 4(3), pp. 209-239.

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

Hinz, O. & Eckert, J. (2010). The Impact of Search and Recommendation Systems on Sales in Electronic Commerce, *Business & Information Systems Engineering*, 2(2), pp. 67–77.

Jamieson, K. H. & Cappella, J. N. (2010). *Echo Chamber: Rush Limbaugh and the Conservative Media Establishment*. Oxford: Oxford University Press.

Jannach, D., Ludewig, M., Lerche, L. (2017). Session-based item recommendation in e-commerce: on short-term intents, reminders, trends and discounts. *User Modeling and User-Adapted Interaction* 27, pp. 351–392.

Kerber, W. (2016). Digital Markets, Data, and Privacy: Competition Law, Consumer Law and Data Protection. *Journal of Intellectual Property Law & Practice*, 11(11), pp. 856-866.

Lee, D. & Hosanagar, K. (2015). "People Who Liked This Study Also Liked": An Empirical Investigation of the Impact of Recommender Systems on Sales Volume and Diversity. Available at: https://www.krannert.purdue.edu/academics/mis/workshop/Rec%20Diversity%20Empirical%20DEC%202015.pdf (Accessed: 02 November 2020)

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. *Information Processing and Management*, 42(4), pp. 1123-1131.

MacKenzie, I.; Meyer, C.; Noble, S. (2013). How retailers can keep up with consumers. McKinsey & Company, Available at: https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-keep-up-with-consumers (Accessed: 20 October 2020).

Milano, S., Taddeo, M., Floridi, L. (2020). Recommender systems and their ethical challenges. *AI & Society*, 6(4), pp. 957-967.

Morgan, B. (2019). 'What Is The Netflix Effect?', Forbes Online, 19 February. Available at: https://www.forbes.com/sites/blakemorgan/2019/02/19/what-is-the-netflix-effect/#7e6dd5025640 (Accessed: 20 October 2020).

Morozovaite, V. (2020). Commercial hypernudging in digital markets: should we worry about consumer choice? Available at: https://law.haifa.ac.il/images/ASCOLA/Morozovaite_paper.pdf (Accessed: 20 October 2020).

Nelson, Philip (1970). Information and Consumer Behavior, *Journal of Political Economy*, 78(2), pp. 311-329.

Obar, J. A. and Oeldorf-Hirsch, A. (2018). The Biggest Lie on the lnternet: Ignoring the Privacy Policies and Terms of Service Policies of Social Networking Services. *Information, Communication & Society*, pp. 1-20.

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 Relevance. *Journal of Computer-Mediated Communication*, 12(3), pp. 801-823.

Pogorelskiy, K. & Shum, M. (2019). News We Like to Share: How News Sharing on Social Networks Influences Voting Outcomes. *Warwick Economics Research Papers,* (1199), pp. 1-48.

Prey, R. (2018). Nothing personal: algorithmic individuation on music streaming platforms. *Media, Culture & Society,* 40(7), pp. 1086-1100.

PwC (2019). Getting personal: Putting the *me* in entertainment and media. Perspectives from the Global Entertainment & Media Outlook 2019-2023. PricewaterhouseCoopers. Available at: https://www.pwc.com/gx/en/entertainment-media/outlook-2019/entertainment-and-media-outlook-perspectives-2019-2023.pdf (Accessed: 6 November 2020).

Rader, E. & Gray, R. (2015), Understanding User Beliefs About Algorithmic Curation in the Facebook News Feed. In: Jinwoo Kim (ed.), *CHI 2015: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, New York: ACM, pp. 173-182.

Senecal, S. & Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. *Journal of Retailing*, 80(2), pp. 159-169.

Stigler, G. J., & Becker, G. S. (1977). De Gustibus Non Est Disputandum. *American Economic Review*, 67(2), pp. 76-90.

Sunstein, C. R. (2009). *Republic.com 2.0*. Princeton: Princeton University Press.

Sunstein, C. R. (2017). *# Republic: Divided Democracy in the Age of Social Media.* Princeton: Princeton University Press.

Taylor, C. R. (2004). Consumer Privacy and the Market for Customer Information. *The RAND Journal of Economics*, 35(4), pp. 631-650.

Wolinsky, Asher (1995). Competition in Markets for Credence Goods, *Journal of Institutional and Theoretical Economics*, 151(1), pp. 117-131.

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

Vanberg, V.J. (2002). Rational Choice vs. Program-based Behaviour – Alternative Theoretical Approaches and their Relevance for the Study of Institutions. *Rationality and Society*, 14(1), pp. 7-54.

Zhang, S., Yao, L., Sun, A. & Tay, Y (2019). Deep Learning Based Recommender System: A Survey and New Perspectives, in: *ACM Computer Surveys*, 52(1), pp. 1-38.

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