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Recommender Systems and Competitive Harm: Emerging Challenges for Competition Policy

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Recommender Systems and Competitive Harm: Emerging Challenges for Competition Policy

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1 Introduction

In the digital era, recommender systems have become central to user engagement on online platforms, shaping how individuals interact with content, products, and services. Their widespread adoption stems from their ability to address key frictions in consumer decision-making, such as search costs (Brynjolfsson et al., 2006; Hinz and Eckert, 2010), information overload (O'Donovan and Smyth (2005)), and choice overload (Bollen et al., 2010), by narrowing options and personalizing suggestions. The outcomes include enhanced user satisfaction (Kim et al., 2021), increased user retention, and revenue growth. For example, Gomez-Uribe and Hunt (2015) report that approximately 80% of content streamed on Netflix is influenced by its recommendation algorithms, while a 2013 McKinsey report found that 35% of Amazon's sales are generated through its recommendation engine (MacKenzie et al., 2013).

There is a vast academic literature on recommendation systems. On the theoretical side, Hagiu and Jullien (2011) show that platform recommendation systems influence seller incentives, which naturally creates opportunities for the platform to bias search results in ways that favor its own objectives. De Corniere and Taylor (2019) explore alternative trade-offs when recommendation bias may harm consumers, while other studies focus on monetizing recommendations (through mechanisms such as the Buy Box or advertising), platform self-preferencing, and directing consumption toward particular sellers (Bourreau and Gaudin (2022), Teh and Wright (2022), Calvano et al. (2025), Ciotti and Madio (2023), Zhou and Zou (2023), Aguiar et al. (2024), Bar-Isaac and Shelegia (2025), among others). On the empirical side, Zhou et al. (2024) demonstrate that higher recommendation precision is not always beneficial, while Donnelly et al. (2024) find that some degree of personalization improves outcomes for all agents compared with a "best-selling" recommendation system. This trade-off is further supported by Dinerstein et al. (2018) and Huang and Xie (2023).[1]

[1]Several additional papers, including Foerderer et al. (2018), Wen and Zhu (2019), He et al. (2020), Lam (2023), Farronato et al. (2023), and Waldfogel (2024), empirically investigate the effects of platform self-preferencing.

Recommender systems have become de facto infrastructure in digital markets, determining visibility, shaping consumer choice, and allocating demand – all critical levers of competition (Calvano et al. (2025)). At the same time, they move platforms away from neutral marketplaces toward curated ones (Burguet et al. (2015)), altering incentives so that recommendation design can harm both buyers and sellers (Donnelly et al. (2024)).[2] Moreover, recommender systems and curated search have expanded across online marketplaces, with new features constantly added; each addition is largely endogenous to the platform, whose incentives may not align with those of buyers or sellers. For these reasons, it is important to examine how a variety of marketplace features interact with competition policy.

In this policy brief, we summarize key issues related to recommendation systems that are relevant for competition policy. We also discuss potential policy interventions and the circumstances under which they are most appropriate.

2 Mechanisms of Competitive Harm

2.1 Self-Preferencing and Strategic Bias in Algorithms

We observe considerable variation in the degree of vertical integration both within and across platform industries. In e-commerce, for example, eBay operates purely as a marketplace, while Amazon itself accounts for roughly 40% of sales on its platform. In the market for mobile apps, Apple and Google distribute their own applications through their app stores. A similar pattern appears in the video game industry, where Microsoft, Nintendo, and Sony sell their in-house titles through their respective digital stores. Looking ahead, the advent of driverless cars could lead Uber to vertically integrate by directly providing rides on its platform. A comparable shift could occur in food delivery, where autonomous vehicles and robotic kitchens may allow platforms like DoorDash or Uber Eats to prepare and deliver

[2] For example, Fletcher et al. (2023) review how bias in recommender systems affects competition among sellers on platforms.

meals themselves.

When platforms vertically integrate, a central concern is that they may exploit their control over recommender and ranking systems to steer consumers toward their own products, a practice known as self-preferencing (De Corniere and Taylor (2014), Condorelli and Padilla (2020), Farronato et al. (2023)). This issue has been a focal point of recent competition policy debates in the EU (Crémer et al. (2019)), as the design and control of recommender systems give platforms the ability to secure an unfair advantage in downstream markets. While platform entry into these markets can, in principle, intensify competition and lower prices, it may also discourage innovation by third-party sellers who find their products disadvantaged by biased recommendation systems, an outcome that ultimately harms consumers (Huang et al. (2013) and Foerderer et al. (2018)).

A key theoretical contribution to the study of self-preferencing is Motta (2023), who analyzes the conditions under which such conduct can foreclose rivals and harm competition. Crucially, Motta shifts the focus away from whether platforms hold "must-have" status and instead highlights the strategic use of preferential placement as a tool for exclusion. His models demonstrate that even when a platform's intermediation service is not indispensable, self-preferencing can still reduce total welfare by limiting consumers' access to better or cheaper alternatives. This perspective clarifies when self-preferencing may amount to an abuse of dominance under competition law and underscores its role as a subtle yet powerful form of vertical foreclosure.

While Motta (2023) provides a rigorous theoretical basis, empirical research has sought to assess the prevalence and competitive effects of self-preferencing in practice. Waldfogel (2024) offers compelling empirical evidence from a large-scale study of Amazon's search rankings. Using a dataset of over 8 million search results across different national Amazon platforms, he finds that Amazon consistently ranks its own products significantly higher than similar third-party listings, on average by 24 positions. Notably, Waldfogel observes that this advantage diminishes following the European Commission's designation of Amazon as a "gatekeeper" under the Digital Markets Act in September 2023, suggesting that regulatory scrutiny can have a measurable impact on platform behavior. His findings lend credence to concerns about algorithmic self-preferencing and illustrate how policy can act as a constraint on platform power.

However, other scholars have called for greater precision in the conceptualization and measurement of self-preferencing. Jürgensmeier and Skiera (2023) argue that the focus on relative ranking positions can obscure more fundamental aspects of platform behavior. They propose a broader definition of recommender-driven visibility, which accounts for the total exposure a product receives across the platform, not just in search results, but also via carousels, notifications, and other algorithmically determined placements. Applying this framework to Amazon marketplaces in three countries, they find little evidence of systematic self-preferencing. Furthermore, their consumer surveys indicate that even if such behavior were more visible, it might not meaningfully change consumer purchasing decisions. This raises an important caveat: self-preferencing may not always result in clear consumer harm, especially when brand trust and convenience outweigh concerns about neutrality.

There are several documented cases of platform self-preferencing in recommender systems. For instance, Google has been fined in both the US and EU for favoring its own products, such as Google Shopping and Google Maps, in search results. Similarly, Amazon has reached a settlement with the EU and faces ongoing litigation with the FTC over self-preferencing in its Buy Box. Moving forward, similar concerns may arise in page and search recommendations within platforms, representing a more subtle but equally effective means of directing consumer attention toward the platform's own offerings.

Self-preferencing is only one manifestation of strategic bias in recommender systems, but it is arguably the most visible, since the platform directly benefits from promoting its own products and capturing sales. Platforms, however, can also pursue their commercial interests in more indirect ways, such as prioritizing products that increase user engagement, drive advertising revenue, or strengthen long-term dependence on the platform. The management and economics literature examines strategic bias as the active influence of consumer behavior by platforms, for instance, by steering users toward preferred products (Hagiu and Jullien (2011) and De Corniere and Taylor (2019)) or by adjusting product exposure at different stages of the purchase journey. For example, Zheng et al. (2009) argue, and Zhang and Bockstedt (2020) empirically show, that substitutes tend to be emphasized during the screening stage, whereas complements are promoted during the purchasing stage.

In one of our studies (Garcia Pires et al. (2025b)), we focus on a novel aspect of strategic bias in a setting where substitute recommendations are particularly relevant, i.e., when consumers are in the screening phase and face product uncertainty. When consumers consider a product, they often lack reliable information about how it will perform, such as its reliability, efficiency, speed, durability, or compatibility. Sellers may attempt to reduce this uncertainty through product descriptions, yet such descriptions are frequently themselves a source of uncertainty.

Recommender systems can help mitigate product uncertainty by exposing consumers to product descriptions or reviews of substitute products, enabling them to draw inferences about the initially inspected product through overlapping features. Contrary to conventional wisdom, however, the benefits of increased exposure to substitute recommendations depend on the type of market. In short-tail, mature, mass markets, recommendations act as an additional competitive force: they drive down prices and thereby raise consumer surplus, consistent with the conventional view. In long-tail, young, niche markets, by contrast, recommendations raise market prices and reduce consumer surplus, making them harmful for consumers. This finding challenges yet another common belief that recommender systems are most beneficial in markets where the cost of discovering alternatives is high.

2.2 Algorithm-Induced Price Effects

With the rise of algorithmic tools, the literature has increasingly turned to examining their impact on market prices. Algorithmic pricing systems adjust prices automatically based on data about competitors, demand, and consumer behavior. Firms typically configure them with objectives such as maximizing sales, profits, or market share, after which the algorithms update prices in real time by learning from past outcomes. For instance, an algorithm may lower prices in response to cheaper competitors or raise them when demand is strong.

In principle, such tools can intensify competition, as a price cut by one firm can trigger almost instantaneous reactions by others' algorithms, creating strong downward pressure and benefiting consumers. At the same time, however, there is a legitimate concern that algorithms may produce the opposite effect: rather than fostering competition, they can "autonomously" learn to sustain higher price levels by shadowing rivals' strategies, effectively mimicking collusion without explicit coordination (Calvano et al. (2025)).

Whether such algorithm-induced behavior should be deemed anti-competitive is to date unclear because some scholars argue that only the use of code to enforce collusion should be seen as a serious threat. What is even more challenging is the fact that potentially anti-competitive behavior has become progressively harder to detect and, in turn to prosecute (Bernhardt and Dewenter (2020)). However, recent developments have provided competition authorities with some tools to address these cases, although algorithm-induced price effects are only deemed illegal if collusion or abuse of dominance can be established (Harrington (2005), Harrington (2006), and Arve et al. (2025)).[3]

Recommender systems raise an even subtler challenge because they do not set prices directly but shape them indirectly through demand steering. The reason is that recommender systems suffer from systemic bias because the underlying data is typically incomplete, selective, and uneven, which leads to misrepresentation of certain users, items, or behaviors in the learning process. Thus, unlike random errors, these biases systematically favor certain products, sellers, or types of content, shaping visibility and consumer behavior that can, in principle, occur even if the platform does not intend to favor specific outcomes. The most

[3]Authorities may analyze price data for abnormal or non-standard distributions that could signal potential collusion. For example, Benford's law characterizes the expected distribution of digits in naturally occurring data. Deviations from this expected distribution in market price data may signal potential collusive behavior.

common types of systemic bias include the popularity bias, where the algorithm disproportionately recommend items that are already popular, the homogeneity bias, which arises because recommendations are disproportionately similar to already consumed goods and the selection bias, where the recommendations reflect the historical interactions of a subset of users.

Although all recommender systems are subject to bias, the type of bias that most strongly shapes the recommendations ultimately depends on the underlying filtering approach, which is clearly under the platform's control. If recommender systems disproportionately direct consumer attention to a small subset of products, they are responsible for increased market concentration, reduce competitive pressure, and thereby upward pricing pressure. While Fletcher et al. (2023) demonstrate that the design of a recommender system, and consequently the presence of specific types of systemic bias, can influence the intensity of seller competition, Garcia Pires et al. (2025b) show more broadly that recommender systems can induce upward pressure on prices even in the absence of systemic bias.

While courts and regulatory investigations have recognized that platforms can deliberately steer users toward preferred products, demonstrating anticompetitive intent is especially challenging when the effects arise from a recommender system, because these impacts are inherently more indirect. However, empirical evidence confirms that these indirect effects matter. For instance, Kaye (2024) find that personalization in online travel agencies helps consumers discover long-tail products, but at the same time enables hotels to charge higher prices, a pattern echoed in Zou and Zhou (2025). These findings illustrate that recommender systems can systematically shift price dynamics by altering the structure of competition, sometimes benefiting consumers through better matches, but often harming them through higher prices.

2.3 Barriers to Entry and Foreclosure

Online marketplaces contain an enormous variety of products and discovery is often a challenge. Recommender systems play a crucial role in facilitating product discovery by helping consumers navigate vast assortments. However, they rely heavily on inputs such as reviews and ratings, which are themselves susceptible to manipulation. Sellers may attempt to game the system to boost their visibility and gain an artificial advantage over competitors, for instance by generating fake reviews or inflating ratings. Vellodi (2018), for example, examines how consumer reviews influence firms' incentives to enter a market and finds that suppressing the reviews of highly-rated incumbents can increase participation by new entrants and consumer surplus. This occurs because newcomers face significant hurdles when competing against established firms that already have favorable ratings.

Recommender systems can exacerbate these distortions, particularly if incumbents' ratings are artificially inflated through fake reviews. Banning fake reviews can therefore be in the platform's own interest, as such manipulation undermines the credibility of its recommender system and can distort the competitive balance among sellers by artificially shifting demand toward lower-quality products. Indeed, Gandhi et al. (2024) argue that regulating the platform in terms of fake reviews can benefit the platform in the long run, which aligns with the Federal Trade Commission's ban on fake and deceptive online reviews and testimonials in October 2024.

However, as previously mentioned, platforms often have an incentive to bias recommendation, especially if they are themselves active in a market as a direct provider. Unlike third-party sellers, platforms can exploit access to marketplace data to gain an unfair advantage, for instance, by imitating successful products (Zhu (2019)). While anecdotal evidence of such practices is abundant, the academic literature remains inconclusive on whether platform entry systematically raises barriers or forecloses markets for third-party providers. For example, Lee and Musolff (2025) find that although Amazon biases its 'Buy Box' toward its own products, overall seller entry is not substantially deterred. By contrast, Cai et al. (2025)

present a more nuanced view, showing that sellers' exit and re-entry decisions depend on their algorithmic ranking. Following the U.K. Competition and Markets Authority's restrictions on Amazon's discretion over 'Buy Box' allocation, sellers with weaker rankings exited top-rated product markets and shifted toward lower-rated niches to diversify their portfolios, possibly explaining the moderate seller exit observed in other studies.

Importantly, biased recommendations can still lead to market foreclosure even when the platform does not act as a direct provider. For instance, Hunold et al. (2020) show that online travel agents condition their search rankings on hotel prices offered through rival platforms. Hotels that charge lower prices on competing platforms are ranked worse, which reduces their willingness to multi-home. A more explicit way of limiting multi-homing is the use of price-parity clauses. Garcia Pires et al. (2025a) highlight that the combination of recommendations and price-parity clauses increases seller exclusivity to one platform, thereby weakening competition between rival platforms and ultimately harming consumers.

Although there are good reasons that barriers to entry and market foreclosure are harmful to consumers, regulatory intervention that fosters market entry does not necessarily have to benefit consumers. If entry is dominated by low-quality sellers, or if it creates additional costs that offset the benefits of increased variety – such as reduced seller visibility – consumer welfare may decline (Ershov (2020)).

2.4 Opacity, Accountability, and Discrimination

Most, if not all, recommendation systems and search algorithms are proprietary. This lack of transparency makes it hard for regulators, sellers, or even consumers to know how decisions are made, let alone challenge them (Abate et al. (2024)). Most recommender systems use a hybrid approach that combines collaborative filtering and content-based filtering. While collaborative filtering considers what similar users have liked in the past, content-based filtering bases relevance on the similarity between items based on their metadata such such as genre, brand, or features. Even without manipulating the recommender system, a platform that is also an active provider can gain a structural advantage over third-party sellers due to its full access to algorithmic rules and comprehensive product data. By ensuring that its own products have complete, high-quality metadata, the platform can achieve higher visibility in content-based filtering. This advantage is further reinforced through collaborative filtering, because early interactions with well-ranked products generate additional exposure through population bias. In contrast, third-party sellers often provide incomplete or suboptimally structured metadata, which limits their visibility and reduces the likelihood of entering this feedback loop.

In a similar vein, platforms often withhold critical information about how recommender systems operate or how data is used, while granting privileged access and features to affiliates or preferred partners. This can include detailed metrics such as click-through rates, engagement data, or insights into ranking factors, which allow favored partners to optimize their products for visibility and relevance. Third-party sellers without such access face uncertainty and reduced ability to compete, skewing discovery and creating competitive asymmetries among sellers.

The significant information asymmetry between market participants, the platform, and regulators creates a strong case for auditability, disclosure standards, and algorithmic oversight. To date, the most extensive auditing efforts have focused on data-sharing agreements aimed at ensuring proper tax compliance. For example, Denmark (Garz and Schneider (2023)), Norway Skatteetaten (2022), and the EU (EU Council Directive 2021/514 commonly known as DAC7) have pursued this with success. These dynamics suggest that auditing recommendation systems, similar to transparency requirements in tax reporting, could help mitigate algorithm-driven disparities and promote fairer competition.

3 Policy and Regulatory Gaps

With the spread of algorithmic pricing tools, regulators quickly focused on the potential for collusion. By contrast, the concerns around recommendation systems are less straightforward. Recommendations can increase concentration and reduce sales, but they often involve a matching component absent in pricing tools. Unlike pricing decisions, which are usually controlled by sellers, recommendation systems are typically managed entirely by the platform.[4]

This creates uncertainty for regulators: is the issue antitrust, consumer protection, or data governance? Such ambiguity can delay policy responses, particularly when responsibilities span multiple authorities or jurisdictions. In this section, we aim to clarify these gaps by examining (i) how existing policies apply to algorithmic tools like recommendation systems, and (ii) potential policy options for addressing emerging challenges.

3.1 Existing Policy Applications to Recommendation Systems

A recent OECD report (OECD (2024)) emphasizes that competition policy in digital markets should remain open to both ex-ante and ex-post instruments. This underscores the challenge of regulating a constantly evolving environment and the need to adapt policies rapidly. While the Federal Trade Commission and the U.S. Department of Justice's recently announced merger guidelines take steps toward providing more tools for digital markets, arguably the most significant regulations are the European Union's Digital Markets Act and Digital Services Act, each playing an important role in governing recommendation systems.[5] The Digital Markets Act primarily aims to preserve competition between platforms (gatekeepers) and their sellers, whereas the Digital Services Act focuses on transparency and

[4] Sellers may influence outcomes through sponsored options, but the system remains largely opaque to them.

[5] Similar rules are followed by Norway's competition authority and the UK's Competition and Markets Authority.

fairness.[6]

Applied to recommendation systems, the Digital Markets Act directly addresses self-preferencing, a key concern discussed in Section 2.1, by aiming to prevent gatekeepers from unfairly favoring their own products or services in search results and recommendations. Under the Digital Markets Act, a gatekeeper cannot prioritize its own offerings in a user's feed simply because they are provided by the gatekeeper or its subsidiaries. In addition, Digital Markets Act obligations prohibit gatekeepers from imposing unreasonable restrictions on other platforms or sellers, or from hindering their operations through algorithmic means. Consequently, recommendation systems should not be influenced by a platform's objectives that account for off-platform competition.[7]

On the transparency front, the Digital Services Act requires online platforms to clearly and understandably explain the main parameters of their recommender systems, including the factors that influence content ranking. The Digital Services Act also obliges platforms to provide users with options to modify or influence these key parameters, giving them greater control over the recommendations they receive. These requirements are similar to transparency measures under California's Consumer Privacy Act and South Korea's AI Framework Act, which impose comparable obligations on artificial intelligence (AI) and algorithmic recommendation systems. In practice, such policies often ensure that platforms offer at least one recommender system that does not rely on profiling users.

3.2 Emerging and Potential Policy Tools

One potential policy approach for regulating recommendation systems is to require public disclosure of their core design parameters, ranking logic, or representative data samples.

[6] In 2023, the European Commission designated six gatekeepers for the first time – Alphabet, Amazon, Apple, ByteDance, Meta, and Microsoft – covering 22 core platform services. Non-compliance can lead to fines of up to 10% of the company's total worldwide annual turnover, up to 20% for repeated infringements, or periodic penalty payments of up to 5% of average daily turnover.

[7] Existing Federal Trade Commission rules apply in a similar manner without new legislation in the U.S., but the Digital Markets Act provides explicit definitions of gatekeepers along with specific rules and obligations tailored to them.

Such transparency would enable independent researchers, competitors, and policymakers to study how these systems operate, reducing the information asymmetry that currently gives platforms a persistent advantage and the potential to harm competitors over time. Evidence from the digital economy shows that controlled data sharing is feasible: platforms like Airbnb, DogVacay, eBay, Expedia, Uber, and Lyft have shared data with researchers, while other studies rely on data collected independently or via third-party aggregators for platforms such as Airbnb, Amazon, Expedia, and rideshare services. These experiences demonstrate that transparency can generate valuable insights without compromising user privacy or platform security. Public access to information could also support the development of fairer, more competitive alternatives, particularly for smaller entrants who lack the data resources and algorithmic tuning capabilities of dominant platforms. So far, we have seen one such case of this in the US where a judge has required Google to allow third party app store competitors access to their app library for three years.[8]

This issue is increasingly relevant as authorities experiment with new regulatory levers, such as the Digital Markets Act and Digital Services Act, as well as emerging fair-ranking obligations in various jurisdictions. Beyond disclosure or the provision of proprietary data or trade secrets, policymakers could explore alternative ways to collect data for public or internal use. For instance, many platforms allow users to request their personal data, creating opportunities to build public databases.[9] Another option is cross-jurisdictional data exchanges, which can address the global scope of large platforms. These measures can be implemented ex-ante, by establishing clear operational rules for recommendation systems, or ex-post, through enforcement when anti-competitive or harmful outcomes are observed. As the policy toolbox evolves, striking the right balance between transparency, competitive neutrality, and incentives for innovation will be critical.

[8]See "Google ordered to open Android to app store rivals after court loss" in the Financial Times, October 7, 2024, for more information.

[9]For example, Uber and Lyft allow both drivers and riders to request their data, and FareFair currently hosts a driver database.

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