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Prosjektet har mottatt midler fra det alminnelige prisreguleringsfondet.

The paradox of platform recommendations: Harmful in markets they are needed most*

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Abstract

We develop a simple extension to the standard Cournot model that allows for competition when some consumers are only aware of one of the two sellers active on a platform. Consumers experience disutility from product uncertainty and the platform can use recommendations to make some of the consumers aware of the other seller which reduces product uncertainty. We show that whether consumers benefit from the platform's policy to recommend a substitute product depends on the underlying market characteristics. Under conditions that characterize short-tail, mature and mass markets, recommendations are beneficial for consumers but the platform has no incentive to provide recommendations. In contrast, under conditions that characterize long-tail, young and niche markets, recommendations are harmful for consumers but the platform has an incentive to provide recommendations. This finding is surprising given the widespread belief that recommender systems are especially valuable in markets where consumers face high costs in discovering alternative products.

Keywords: Marketplaces, Recommendation Systems, Cournot Model

JEL Classification:

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1 Introduction

In the era of digitalization, recommender systems have become a cornerstone of user engagement on online platforms, shaping how individuals interact with content, products, and services. The reason for their widespread use is that they address core frictions in consumer decision-making, such as search costs (Brynjolfsson et al., 2006; Hinz and Eckert, 2010), information overload (O'Donovan and Smyth, 2005; Häubl and Trifts, 2000), and choice overload (Bollen et al., 2010), by narrowing down options and personalizing suggestions. The consequences are, i.a., enhanced user satisfaction (Kim et al., 2021), increased user retention, and revenue growth. For instance, according to Gomez-Uribe and Hunt (2015) approximately 80% of the content streamed on Netflix is influenced by its recommendation algorithms. Similarly, a 2013 McKinsey report noted that 35% of Amazon's sales are generated through its recommendation engine (MacKenzie et al., 2013).

Besides these generally positive aspects, the literature has often focused on potential biases of recommender systems. The computer science literature has typically focused on systemic bias that arise irrespective of the underlying filtering approach. At the most general level, recommender systems can be classified into two core types: collaborative filtering and content-based filtering.[1] Collaborative filtering generates personalized suggestions by analyzing patterns in user-item interactions, focusing on who interacted with which items and how, such as through ratings, purchases, or clicks. A familiar example is Amazon's "Users who viewed this also viewed…" section. Content-based filtering generates suggestions by matching item features, such as category, brand, price, or keywords, to a user's preferences. Unlike collaborative filtering, it focuses on what the items are based on attributes, brand, price, keywords, or descriptions. A common example is Amazon's "Compare with similar items" section. Recommender systems suffer from systemic bias because the underlying data

[1] Frequently, hybrid filtering is mentioned as a third type. Hybrid filtering combines techniques, typically collaborative and content-based filtering, to leverage their strengths and mitigate challenges common in collaborative filtering, such as the cold-start problem, and in content-based systems, like overly narrow recommendations.

is typically incomplete, selective, and uneven, which leads to misrepresentation of certain users, items, or behaviors in the learning process. Examples are the popularity bias, where already popular items are disproportionately recommended, and the exposure bias, where items that are shown more frequently are more likely to be interacted with (Häubl and Trifts, 2009; Chen et al., 2023; Calvano et al., 2025). Such biases can lead to a feedback loop that limits diversity, reinforces existing preferences, and marginalizes niche content or minority perspectives.

In addition, the management and economics literature has analyzed biases that arise due to a platform's design and strategic choices. Design bias can arises because the platform has to determine, for example, the filtering approach, which defines the nature and extent of systemic biases (Fletcher et al., 2023), or the attributes the algorithm should prioritize, which can shape user preference persistantly (Häubl and Murray, 2003). Strategic bias arises whenever platform's actively influence consumer behavior, for example, by steering consumers toward desired products (De Corniere and Taylor, 2019; Hagiu and Jullien, 2011), or exposing consumers to certain product-relationship types during different stages of their purchase. For example, Zheng et al. (2009) argue and Zhang and Bockstedt (2020) empirically find that substitutes are preferred during screening, while complements are favored during purchasing.

In this study, we abstract from any systemic or design bias and instead focus on a novel aspect of strategic bias in a setting where substitute recommendations are most relevant to consumers, i.e., when consumers are in the screening phase. Such recommendations are typically generated by both collaborative filtering, when similar users have viewed substitute products, and by content-based filtering, when products share similar characteristics. Specifically, we focus on a situation in which product uncertainty is the main friction. When consumers show interest in a product there are usually gaps in understanding how the product will perform due to lack of information, for instance, about reliability, efficiency, speed, durability or compatibility. Typically, sellers can reduce this performance uncertainty by providing information through a product description. However, product description is in itself often a source of uncertainty even if sellers are willing to truthfully describe the product. For example, sellers might just be unable to accurately describe the technical details of the product or might simply be unaware of hidden product defects (Dimoka et al., 2012). In offline markets, individuals can physically evaluate products by inspecting or testing them. However, in online markets, individuals suffer from the inability to mitigate product uncertainty through inspecting and testing.

In our model, the recommender system can help mitigate product uncertainty. The theoretical model is build on two sellers that engage in Cournot competition by offering their homogenous product through a platform. Consumers are heterogeneous in their valuations for the product and arrive exogenously either on one or both of the sellers' product pages. Consumers derive utility from consumption, but utility is uncertain because a seller's product page cannot provide sufficient information that fully eliminates uncertainty. However, whenever consumers are exposed to the information on the product page of the substitute product will product uncertainty be reduced. The reason is that information provided on a different product page serves to fill in information gaps. Although substitute products are not identical they typically share overlapping features that allow consumers to infer either directly from the substitute product's description or indirectly from user reviews the performance or the reliability of the initial product. Platforms can therefore help reduce product uncertainty by recommending substitute products to those consumers that only arrive on a single product page.

Our analysis highlights that higher exposure of consumers to recommendations of a substitute product is not necessarily beneficial for consumers. The reason is that although a higher exposure to recommendations increases competition between sellers which tends to decrease the market price and thus benefits consumers, the reduction in uncertainty also increases consumers' willingness to purchase which tends to increase the market price. Which of these effects dominates depends on several conditions: (i) the degree to which product uncertainty is reduced, (ii) the platform's costs related to making recommendations, (iii) arrival rates on the product pages, and (iv) the distribution function of consumer valuations, i.e, market demand.

The analysis allows us to relate the derived conditions to specific market characteristics. First, short-tail, mature and mass markets are typically characterized by log-concave demand, which means that consumer preference are well-established, or low informational value of recommendations because products are already well-known or existing product descriptions are sufficiently informative, which means that the reduction in product uncertainty is negligible. In such markets, recommendations primarily function as additional competitive force, which drives down prices and, in turn, increase consumer surplus.

Second, long-tail, young and niche markets are typically characterized by log-convex demand, which means that willingness to pay is widely dispersed, and low arrival rates, which makes it costly for the platform to provide accurate recommendations. In such markets, recommendations increase the market price and, in turn, decreases consumer surplus. In other words, recommendations are harmful for consumers in long-tail, young and niche markets.

Third, we analyze whether or not the platform benefits from exposing consumers to recommendations and in which markets. We show that in short-tail, mature and mass markets, the platform has an incentive to provide recommendations in high-cost segments, but does not benefit from making recommendations in low-to-intermediate cost segments. As consumers benefit from recommendations in short-tail, mature and mass markets, there is a misalignment of interests between the platform and consumers in low-to-intermediate cost segments. Moreover, in long-tail, young and niche markets, the platform has an incentive to provide recommendation in low-cost segments, the dominant cost segment due to the predominantly digital production, interests of consumers and the platform are generally misaligned because recommendations are harmful to consumers in such markets. This result is quite surprising because the common notion is that recommender systems are particularly beneficial in markets in which it is very costly for consumers to discover alternative products.

2 Model

2.1 The Basic Framework

The goal of our model is to develop a simple microfounded environment where consumers derive utility from consumption of homogeneous products. However, prior to consumption, they face uncertainty about product valuation. Product uncertainty can arise even in the context of homogeneous products when sellers do not provide sufficient information for consumers to fully assess the product's characteristics prior to purchase.[2] Moreover, even when full information is provided, consumers may still face uncertainty about key attributes as is the case for experience or credence goods, where aspects such as fit, usability, or performance, can – if at all – only be evaluated through actual use[3]

We microfound consumer demand with uncertainty by assuming consumer's utility function is exponential:[4]

$$U(v) = 1 - e^{-\alpha_p(v-P-\alpha_r\psi)},$$

where v is the certain stand-alone utility earned from the product, P is the price, and ψ is a

[2]For example, Dimoka et al. (2012) highlight that sellers may be unable to fully describe the product due to inherent limitations of online interfaces that constrain the richness and completeness of product descriptions, may be unaware of hidden defects, or may just be unwilling to provide an accurate description.

[3]Generous return policies can significantly reduce product uncertainty, particularly for experience goods. However, such policies are not uniformly adopted across e-commerce platforms. Amazon stands out in this regard, yet even on Amazon, where Fulfilled by Amazon (FBA) products offer free and convenient returns, uncertainty can persist due to variability among third-party sellers who do not use FBA. Moreover, uncertainty is not fully eliminated even for FBA products because, for many goods, quality or performance can only be reliably assessed after prolonged use. Examples include battery life in electronics, material resilience of kitchen appliances, durability of luggage, and wear of apparel.

[4]Economic modeling of behavior under uncertainty has almost exclusively used one of two approaches. The mean-variance approach assumes that agents evaluate risky prospects solely based on expected return and variance, which is appropriate when utility is quadratic or when returns are normally distributed. The alternative approach uses a specific function to assess expected utility which is either the exponential utility function, with constant absolute risk aversion, or the power utility function with constant relative risk aversion (Phelps, 2024). We follow the second approach and assume an exponential utility function for two reasons. First, because expenses for platform purchases are typically small relative to individual wealth, it is reasonable to assume constant absolute risk aversion, as wealth effects on risk preferences are negligible. For example, a report by Forbes (Forbes Insight, 2016) highlights that while consumers often use online channels to research major products, typically high-value, durable, or high-involvement goods, they generally prefer to complete the actual purchase in physical retail locations and not online. Second, in our setting, the mean-variance approach restricts the demand function to be linear, which is not an innocuous assumption. The resulting loss of generality will become clear later.

random variable that captures the uncertainty over the product's valuation. The parameters α_p and α_r capture consumers' price, respectively risk, sensitivity.

We assume ψ is normally distributed with mean zero and variance σ_H^2, i.e., $\psi \sim \mathcal{N}(0, \sigma_H^2)$. The assumption of a normal distribution allows us to use the moment-generating function of a normal distribution to express expected utility as follows:[5]

$$\mathbb{E}[U] = 1 - e^{-\alpha_p(v-P)} \cdot \mathbb{E}[e^{\alpha_p \alpha_r \psi}] = 1 - e^{-\alpha_p(v-P)} e^{\frac{1}{2}\alpha_p^2 \alpha_r^2 \sigma_H^2} = 1 - e^{-\alpha_p(v-P)} e^{\alpha_\sigma \sigma_H^2}, \qquad (1)$$

where $\alpha_\sigma = \frac{1}{2}\alpha_p^2 \alpha_r^2$. Equation (1) illustrates that a higher variance reduces a consumer's expected utility and thus her willingness to pay for the product.

We assume there are two producers (seller 1 and seller 2) whose products are only available through a platform. To incorporate market power at the product level, we assume sellers engage in quantity competition but generalize the Cournot model to allow for awareness of potentially only one product. In practice, consumers observe a variety of products and arrive on product pages in different ways depending on how they search. For example, if a consumer is interested in an exercise bike, they may go to the platform and type "exercise bike" into platform's search bar. Alternatively, they may search for "exercise bike" on a search engine, web browser, AI tool, or social media and be directed to a specific product page within the platform without seeing any other products on the platform. Thus, we assume that consumers are exogenously divided into four masses: a mass ϕ_0 that does not land on any product page, a mass ϕ_1 (ϕ_2) that only observes seller 1's (seller 2's) product, and a mass $1 - \phi_0 - \phi_1 - \phi_2$ that observes both products, where $\phi_0 + \phi_1 + \phi_2 \in [0, 1]$.

The platform can distinguish between consumer types and use recommendations on product pages to increase the number of consumers that see both products. We operationalize this by assuming the platform chooses to recommend to a fraction, $1 - \lambda_i$, $\lambda_i \in [0, 1]$, of individuals that arrive only on seller i's product page, seller j's product on product page i.

[5] We are not the first to use such an approach when consumers dislike uncertainty (Karni and Schmeidler (1991), Balvers and Szerb (1996), Gul and Pesendorfer (2014), Heyes and Martin (2016)).

Hence, only the share $\phi_i\lambda_i$ is soley aware of product i. Likewise, only the share $\lambda_j\phi_j$ is soley aware of product j, while the remaining individuals that land on at least one product page, the share $1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j$, is aware of both products. In the extreme case where $\lambda_i=0$, the platform makes all consumers on the platform aware of both products, which resembles the standard Cournot setting.

A recommendation is directly beneficial to consumers because we assume that it reduces the uncertainty related to the product from σ_H^2 to σ_L^2, where we denote $\Delta=\sigma_H^2-\sigma_L^2>0$. In other words, product uncertainty is reduced whenever consumers are exposed to the information provided on the product page of a substitute. This is because such information can help fill existing knowledge gaps either directly through product descriptions with complementary information or indirectly through user reviews.[6] Platforms can therefore mitigate product uncertainty by recommending substitute products to consumers who initially view only a single product page.

Consumers differ in their stand-alone value. Suppose that the stand-alone value is distributed according to a cumulative distribution function $G(v)$ and density function $g(v)$, with $\bar{v}$ and $\underline{v}$ denoting the upper and lower limits of the support. We assume that consumers purchase the product if their expected utility is non-negative, i.e., $E(U(v))\geq 0$, which implies that the last consumers to purchase the product are given by $E(U(v^*))=0$. Hence, the marginal consumers are determined by

$$1-e^{-\alpha_p(v_i^*-P)}e^{\alpha_\sigma\sigma_i^2}=1-e^0=0 \quad\Leftrightarrow\quad v_i^*=P+\frac{\alpha_\sigma}{\alpha_p}\sigma_i^2, \quad i=H,L \tag{2}$$

Because consumers are distributed accoring to $G(v)$ this implies that $Q=(\lambda_i\phi_i+\lambda_j\phi_j)[1-$

[6]Our assumption of product homogeneity neither precludes the existence of product uncertainty nor the possibility of reducing it through recommendations. In fact, some degree of homogeneity is necessary for related product information to be useful, as only then do products share overlapping features that enable consumers to infer relevant characteristics of the original product. Importantly, homogeneity does not imply that consumers can easily understand a product's functionality. Although complex products are typically multi-attribute and offer greater potential for differentiation, even homogeneous products often possess multi-attribute characteristics that are insufficiently disclosed or understood by consumers. Moreover, differentiation is ultimately a strategic choice by firms, but we abstract from it as it is not essential in our context.

$G(v_H^*)] + (1 - \phi_0 - \lambda_i\phi_i - \lambda_j\phi_j)[1 - G(v_L^*)]$.

Some consumers only see one product page (the shares $\lambda_i\phi_i$ and $\lambda_j\phi_j$), while the remaining consumers (the share $1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j$) see two product pages. These groups differ in their size because only the latter group benefits from reduced uncertainty, which implies different cut-offs. This generates a demand curve with the following relation:

$$\frac{dQ}{dP} = -[(\lambda_i\phi_i + \lambda_j\phi_j)g(v_H^*) + (1 - \phi_0 - \lambda_i\phi_i - \lambda_j\phi_j)g(v_L^*)] < 0. \tag{3}$$

We assume that the sellers are unable to observe the type of consumer. This means that seller i chooses the single output q_i which is the sum of seller i's output sold to exclusive consumers, q_i^E, and the output sold to consumers that consider both competing sellers, q_i^C, so that $q_i = q_i^E + q_i^C$. Altogether, this implies that demands are given by:

$$q_i^E = \lambda_i\phi_i [1 - G(v_H^*)] \text{ for } i = 1, 2, \tag{4}$$

$$q_i^C + q_j^C = (1 - \phi_0 - \lambda_i\phi_i - \lambda_j\phi_j)[1 - G(v_L^*)], \text{ for } i \neq j. \tag{5}$$

Sellers are symmetric in their marginal costs, c, and face the same ad valorem fee charged by the platform, f. Thus, seller i maximizes profit with respect q_i where profit is given by

$$\pi_i = [(1 - f)P - c] \cdot q_i. \tag{6}$$

The platform takes its fee as given when selecting its within product recommendation system.[7] Thus, the platform maximizes profit from the two products with respect to λ_1 and λ_2 where profit is given by

$$\Pi = f \cdot PQ - \kappa(\lambda_i, \lambda_j), \tag{7}$$

where $Q = q_1 + q_2$ and $\kappa(\lambda_i, \lambda_j)$ is a convex cost related to providing recommendations.

[7]In practice, marketplace platforms set fees at an aggregated level (Tremblay (2021)), while recommendations within product pages are personalized (Chen and Tsai (2023)).

2.2 Market Equilibrium

We solve the game backwards by first considering the problem of the sellers, taking λ_1 and λ_2 as given. Hence, our solution concept is the Subgame Perfect Nash Equilibrium.

Differentiating equation (6) with respect to q_i yields the equilibrium seller output which reads

$$q_i^* = (P - C)[\lambda_i \phi_i g(v_H^*) + (1 - \phi_0 - \lambda_i \phi_i - \lambda_j \phi_j) g(v_L^*)]. \tag{8}$$

Using the fact that $Q = q_i + q_j$ yields the equilibrium market output given by[8]

$$Q^* = (P - C)\left[(\lambda_i \phi_i + \lambda_j \phi_j) g(v_H^*) + 2(1 - \phi_0 - \lambda_i \phi_i - \lambda_j \phi_j) g(v_L^*)\right], \tag{9}$$

where $C = \frac{c}{1-f}$. Equation (9) allows us to analyze how equilibrium quantity is affected by a higher visibility of product j on product page i, i.e., a higher exposure of consumers to recommendations of product j, which is given by[9]

$$\frac{dQ}{d\lambda_i} = \frac{(P-C)\left[(\lambda_i\phi_i + \lambda_j\phi_j) g(v_H^*) + (1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j) g(v_L^*)\right]\phi_i\left[g(v_H^*) - 2g(v_L^*)\right]}{2(\lambda_i\phi_i+\lambda_j\phi_j) g(v_H^*)\left[1 + \frac{P-C}{2}\frac{g'(v_H^*)}{g(v_H^*)}\right] + 3(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j) g(v_L^*)\left[1 + \frac{2(P-C)}{3}\frac{g'(v_L^*)}{g(v_L^*)}\right]}. \tag{10}$$

To ensure stability, we assume that the marginal feedback of quantity on itself through the price mechanism is sufficiently weak, which means that the denominator is positive. Hence, a sufficient condition to ensure stability, i.e., that market quantity responds predictably to changes, is $\frac{g'(v)}{g(v)} \geq -\frac{3}{2(P-C)}$, which means that $g(v)$ is either log-convex or if log-concave only mildly log-concave. We summarize in:

Assumption 1. *The distribution $g(v)$ is not too log-concave and therefore the ratio $\frac{g'(v)}{g(v)}$ is not too decreasing on $[\underline{v}, \bar{v}]$.*

With the help of Assumption 1, we can establish whether increased exposure of consumers to recommendations of substitute product j (a decrease in λ_i) increases or decreases

[8] See appendix A.1 for a derivation of the equilibrium quantity.

[9] A full derivation can be found in appendix A.1.

equilibrium quantity. We summarize in:

Proposition 1. *Under Assumption 1, increased exposure of consumers to recommendations of a substitute product (a decrease in λ_i) increases equilibrium quantity if $g(v)$ is either mildly log-convex or mildly log-concave. In contrast, equilibrium quantity decreases if $g(v)$ is strongly log-convex.*

Proof. See Appendix A.2 □

Proposition 1 shows that the effect of recommendations on equilibrium quantity is not as straightforward as one might think. While recommendations increase competition between firms, which tends to reduce the equilibrium price, there is a counteracting effect that emerges due to the direct benefit that consumers gain from reduced uncertainty related to additional information. This direct benefit increases consumers' willingness to pay for the products and tends to increase the equilibrium price. Proposition 1 summarizes the conditions when either of the effects dominates but it is helpful to illustrate that it is indeed consumers' direct benefit from recommendations that causes the ambiguity. To see this, suppose $\Delta = 0$ meaning that recommendations do not reduce uncertainty. Then, consumers' willingness to pay does not change when exposed to a recommendation, i.e., $v_H^* = v_L^*$. In this case, we immediately see that

$$\left.\frac{dQ}{d\lambda_i}\right|_{\Delta=0} = -\frac{(P-C)\,(1-\phi_0)\phi_i[g\left(v_H^*\right)]^2}{g\left(v_H^*\right)\left\{2(\lambda_i\phi_i+\lambda_j\phi_j)\left[1+\frac{P-C}{2}\frac{g'\left(v_H^*\right)}{g\left(v_H^*\right)}\right]+3(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)\left[1+\frac{2(P-C)}{3}\frac{g'\left(v_H^*\right)}{g\left(v_H^*\right)}\right]\right\}} \quad (11)$$

is less than 0, which means that a higher exposure to recommendations of a substitute product j (a lower λ_i) clearly increases equilibrium quantity.

Given the dependence of Proposition 1's results on the shape of the distribution function, it is worthwhile to analyze how greater exposure to recommendations affects consumer surplus, which is given by

$$\begin{aligned} CS &= Q\int_{v_H^*}^{\bar{v}} \left(1 - e^{-\alpha_p(v-P)} e^{\alpha_\sigma \sigma_H^2}\right) g(v)dv \\ &+ (1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)Q\int_{v_H^*}^{\bar{v}} e^{-\alpha_p(v-P)} e^{\alpha_\sigma\sigma_H^2}\left(1-e^{-\alpha_\sigma\Delta}\right) g(v)dv \\ &+ (1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)Q\int_{v_L^*}^{v_H^*} \left(1 - e^{-\alpha_p(v-P)} e^{\alpha_\sigma \sigma_L^2}\right) g(v)dv. \qquad (12) \end{aligned}$$

Equation (12) shows that all individuals that decide to purchase (individuals with $v \geq v_H^*$) receive non-zero utility captured by the first term. In addition, individuals that see two product pages receive a higher utility because of the reduction in uncertainty captured by the second term. Finally, reduced uncertainty implies that individuals that would not have purchased in the absence of a recommendation decide to purchase (individuals with $v_H^* \geq v \geq v_L^*$) because their willingness to pay increases which is captured by the third term.

Differentiating consumer surplus with respect to λ_i yields

$$\begin{aligned} \frac{\partial CS}{\partial \lambda_i} &= \frac{\partial Q}{\partial \lambda_i}\int_{v_H^*}^{\bar{v}} \left(1 - e^{-\alpha_p(v-P)} e^{\alpha_\sigma \sigma_H^2}\right) g(v)dv - Q\int_{v_H^*}^{\bar{v}} \alpha_p e^{-\alpha_p(v-P)} e^{\alpha_\sigma\sigma_H^2}\frac{\partial P}{\partial Q}\frac{\partial Q}{\partial \lambda_i} g(v)dv \\ &+ \left[(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)\left(1+\alpha_p Q\frac{\partial P}{\partial Q}\right)\frac{\partial Q}{\partial \lambda_i} - \phi_i Q\right]\int_{v_H^*}^{\bar{v}} e^{-\alpha_p(v-P)} e^{\alpha_\sigma\sigma_H^2}\left(1-e^{-\alpha_\sigma\Delta}\right) g(v)dv \\ &+ \left[(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)\frac{\partial Q}{\partial \lambda_i} - \phi_i Q\right]\int_{v_L^*}^{v_H^*} \left(1 - e^{-\alpha_p(v-P)} e^{\alpha_\sigma \sigma_L^2}\right) g(v)dv \\ &- (1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)Q\frac{\partial P}{\partial Q}\frac{\partial Q}{\partial \lambda_i}\int_{v_L^*}^{v_H^*} \alpha_p e^{-\alpha_p(v-P)} e^{\alpha_\sigma\sigma_L^2} g(v)dv. \qquad (13) \end{aligned}$$

Obviously, the effect of a higher visibility of substitute product j on product page i has an ambiguous effect on consumer surplus because the effect on equilibrium quantity is ambiguous. Yet, the effect on consumer surplus can be signed under specific conditions.

In the absence of a direct benefit of recommendations for consumers, i.e., $\Delta = 0$, consumer surplus reduces to

$$\frac{\partial CS}{\partial \lambda_i}|_{\Delta=0} = \frac{\partial Q}{\partial \lambda_i}\int_{v_H^*}^{\bar{v}}\left(1-e^{-\alpha_p(v-P)}e^{\alpha_\sigma\sigma_H^2}\right)g(v)dv - Q\int_{v_H^*}^{\bar{v}}\alpha_p e^{-\alpha_p(v-P)}e^{\alpha_\sigma\sigma_H^2}\frac{\partial P}{\partial Q}\frac{\partial Q}{\partial \lambda_i}g(v)dv. \quad (14)$$

Because $\frac{\partial P}{\partial Q} < 0$ and $\frac{\partial Q}{\partial \lambda_i}|_{\Delta=0} < 0$, we get that $\frac{\partial CS}{\partial \lambda_i} < 0$, which means that a higher exposure to recommendations on product page i (a reduction in λ_i) increases consumer surplus.

Moreover, if $\frac{\partial Q}{\partial \lambda_i} < 0$, which according to Proposition 1 happens if $g(v)$ is either mildly log-concave or mildly log-convex, then all terms but the third in equation (13) are negative. With the additional condition that α_p is not too large, which ensures that the term $\left(1-\alpha_p Q\frac{\partial P}{\partial Q}\right)$ is positive, a higher exposure to recommendations on product page i (a lower λ_i) increases consumer surplus.

Finally, and arguably most interesting, we investigate the possibility that a higher exposure to recommendations on product page i reduces consumer surplus. Proposition 1 suggests that this may be possible because a higher exposure to recommendations can indeed decrease the equilibrium quantity. Hence, the question arises which other conditions are required for $\frac{\partial CS}{\partial \lambda_i} > 0$ to emerge. Equation (13) shows that if $\frac{\partial Q}{\partial \lambda_i} > 0$, there are only two ambiguous terms, the third and the fourth, while the remaining terms are positive. If α_p is sufficiently small, $\frac{\partial CS}{\partial \lambda_i}$ will be positive if $(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)\frac{\partial Q}{\partial \lambda_i} - \phi_i Q \geq 0$. For the inequality to hold, stronger log-convexity of $g(v)$ than that for ensuring $\frac{\partial Q}{\partial \lambda_i} > 0$ is required. We summarize these results in the following proposition:

Proposition 2. *A higher exposure to recommendations of a substitute product is*

(i) beneficial for consumers if the reduction in uncertainty is negligible ($\Delta = 0$),

(ii) beneficial for consumers if price sensitivity is not too high (sufficiently low α_p) and $g(v)$ is either mildly log-concave or mildly log-convex,

(iii) harmful for consumers if price sensitivity is not too high (sufficiently low α_p) and $g(v)$ is sufficiently log-convex.

Proposition 2 provides two key insights into the impact of recommendations on consumer welfare. First, when market demand is log-concave (or only mildly log-convex) or when recommendations do not provide additional valuable information, consumers benefit from increased recommendations.[10] Second, when market demand is strongly log-convex, recommendations are detrimental to consumer welfare. To understand the broader implications of these results, we relate these analytical conditions to specific market characteristics.

Log-concave demand structures are commonly associated with mature or mass markets because consumer preferences are well-established. Such preferences are often seen in short-tail markets where demand is usually concentrated around widely recognized, i.e., generic, products, with negligible sales for more specialized products.[11] In addition, the informational value of recommendations is often minimal in short-tail, i.e., mature or mass, markets either because products are already well-known or existing product descriptions, reviews, and brand recognition are sufficiently informative.[12] Hence, recommendations function as an additional competitive force, which drives down prices and increase, in turn, consumer surplus.

In contrast, young or niche markets tend to exhibit a wide dispersion of willingness to pay across consumers.[13] Diverse and less established consumer preferences are often seen in markets with long tails, which the literature has desribed by power-law sales distributions (Brynjolfsson et al., 2003; Chevalier and Goolsbee, 2003). Power-law sales distributions strongly suggest a log-convex demand structure, because they reflect a heavy-tailed distribution of demand, where some products maintain demand at high prices instead of demand dropping sharply.

Our results have significant implications for the consumer welfare effects of recommender

[10]This is true even if recommendations are asymmetric across sellers, $\lambda_1\phi_1 \neq \lambda_2\phi_2$, which is consistent with results from Bairathi et al. (2025).

[11]For example, Parker and Neelamegham (1997) show that category sales become less sensitive to price changes as they reach the mature stages of the life cycle which is suggestive of log-concave market demand. Moreover, Elberse (2008) finds that over time although the tail lengthens, it does also flatten, with higher sales concentration at the head of the distribution meaning that the importance of individual best sellers is not diminishing but growing over time.

[12]Taeuscher (2019) finds that high consumer uncertainty shifts demand toward more reputable producers and products, reducing the long-tail effect. This supports the idea that uncertainty is more pronounced in long-tail markets.

[13]See, for example, Larson (2013) who analyzes product design where "generic" products refer to a low dispersion of consumer valuations for the product and "niche" products to a high dispersion.

systems. Conventional wisdom suggests that these systems are particularly valuable in young or niche markets, where limited information makes informed purchasing decisions costly for consumers.[14] By reducing search costs and aiding decision-making, recommendations help navigate unfamiliar product landscapes. While direct studies linking recommendation systems to young markets are scarce, existing literature broadly supports their value in environments with high information scarcity.[15]

Surprisingly, our findings challenge this presumption. While young and niche markets are precisely where recommendations are thought to be most beneficial by helping consumers discover relevant alternative products, our analysis suggests that under these very conditions, recommendations actually harm consumers. This paradox highlights the need to account for market characteristics when assessing their overall impact on consumer welfare because the possibility of upward pressure on prices has typically not been anticipated.

While our previous analysis focused on consumers, we will analyze in what follows how sellers are affected if the platform increases consumers' exposure to a substitute product. We begin by investigating how higher exposure to substitute product j affects seller i's profits, which is given by

$$\frac{\partial \pi_i}{\partial \lambda_i} = (1-f)\left[(P-C)\frac{\partial q_i}{\partial \lambda_i} + \frac{\partial P}{\partial Q}\frac{\partial Q}{\partial \lambda_i} q_i\right]. \tag{15}$$

Using equations (8) and (9), we can derive how seller i's quantity and the market price are

[14] Unlike mature or mass markets, where historical data provides a reliable basis for recommendations, young or niche markets face significant challenges due to data scarcity, rapidly changing product assortments, and limited consumer familiarity. These conditions give rise to the cold-start problem, where a lack of sufficient user-item interaction history hampers collaborative filtering approaches, while content-based methods struggle due to the absence of comparable products or rich metadata. Without well-established user preferences or comprehensive product descriptions, platforms must invest heavily in alternative strategies, such as manual curation, hybrid models, or incentivized data collection (Bobadilla et al., 2013; Schein et al., 2002). As a result, the costs associated with generating accurate recommendations tend to be higher, and platforms struggle to provide precise, meaningful suggestions.

[15] Zhu and Zhang (2010) show that niche market producers heavily rely on online consumer reviews to increase sales due to the scarcity of available information about niche products. Although their analysis is in context of online review systems, our setting is similar because recommender systems that expose consumers to substitute products provide additional information either directly through the substitute product's description or indirectly from user reviews about performance or reliability that allow consumers to draw inferences about the original product.

affected by a change in λ_i to arrive at

$$\frac{\partial \pi_i}{\partial \lambda_i} = (1-f)(P-C)\, q_i^* \phi_i \left[\frac{g(v_H^*) - g(v_L^*)}{\Omega_1} - \frac{g(v_H^*) - 2g(v_L^*)}{\Omega_2} \right], \tag{16}$$

$$\begin{aligned}
\Omega_1 &= 2\lambda_i \phi_i g(v_H^*) \left[1 + \frac{(P-C)}{2} \frac{g'(v_H^*)}{g(v_H^*)} \right] + 2(1 - \lambda_i\phi_i - \lambda_j\phi_j) g(v_L^*) \left[1 + \frac{(P-C)}{2} \frac{g'(v_L^*)}{g(v_L^*)} \right] \\
\Omega_2 &= 2(\lambda_i\phi_i + \lambda_j\phi_j) g(v_H^*) \left[1 + \frac{P-C}{2} \frac{g'(v_H^*)}{g(v_H^*)} \right] + 3(1 - \lambda_i\phi_i - \lambda_j\phi_j) g(v_L^*) \left[1 + \frac{2(P-C)}{3} \frac{g'(v_L^*)}{g(v_L^*)} \right],
\end{aligned}$$

where $\Omega_2 \geq \Omega_1 > 0$. Equation (16) allows us to derive a couple of results, which we summarize in the following proposition:

Proposition 3. *Under Assumption 1, a higher exposure of consumers to recommendations on product page i of a substitute product j is harmful for seller i except when both market demand is log-concave and seller i has a sufficiently large visibility disadvantage.*

Proof. See Appendix A.3 □

Whether seller i benefits from a higher exposure of consumers to recommendation of substitute product j depends on the informational value of recommendations Δ, the shape of the distribution function $g(v)$, and the product visibility of the sellers ($\lambda_i\phi_i$ and $\lambda_j\phi_j$). Generally, a higher exposure of consumers to recommendations of substitute product j is harmful for seller i because it only lures away consumers to the competitor. However, if demand is log-concave seller i benefits if the platform recommends substitute product j on seller i's product page. The intuition for this result is as follows. If demand is log-concave, then seller i's produced quantity increases when λ_i decreases and therefore also seller i's profits. Consequently, total quantity produced also increases which leads to a decrease in the market price counteracting the positive effect on seller i's profits. However, if visibility is very asymmetrically skewed toward seller j, the positive effect becomes very large such that the overall effect on seller i's profits is positive. Hence, a small seller can actually benefit if a large competitor's product is recommended on her product page but this happens only in short-tail, mature and mass markets.

In the same vein, we can analyze how a higher exposure of consumers to product i on product page j affects seller i's profits, which is given by

$$\frac{\partial \pi_i}{\partial \lambda_j} = (1-f)\left[(P-C)\frac{\partial q_i}{\partial \lambda_j} + \frac{\partial P}{\partial Q}\frac{\partial Q}{\partial \lambda_j} q_i\right]. \tag{17}$$

Again, using equations (8) and (9), we can derive how seller i's quantity and the market price are affected by a change in λ_j to arrive at

$$\frac{\partial \pi_i}{\partial \lambda_j} = -(1-f)\,(P-C)\,q_i^* \phi_j \left[\frac{g\left(v_L^*\right)}{\Omega_1} + \frac{g\left(v_H^*\right) - 2g\left(v_L^*\right)}{\Omega_2}\right]. \tag{18}$$

Equation (18) allows us to derive a couple of results, which we summarize in the following proposition:

Proposition 4. *Under Assumption 1, a higher exposure of consumers to recommendations on product page j of a substitute product i is beneficial for seller i except when both market demand is log-concave, and seller j has a sufficiently large visibility disadvantage.*

Proof. See Appendix A.4 □

Proposition 4 illustrates that sellers are essentially mirror-wise affected by the platform's recommendation policy depending on which product benefits from enhanced visibility. In other words, a large seller can actually be harmed if the platform recommends her product on a small seller's product page but this only happens in short-tail, mature and mass markets. Our analysis made it clear that either seller can benefit both from recommendations of their own and from their competitor's product and this crucially depends on the market characteristics and seller size. In the next section, we derive the optimal platform policies to analyze in which markets the platform has a greater interest to increase the exposure to recommendations of a substitute product.

2.3 Optimal Platform Policies

Differentiating the platform's profits with respect to λ_i yields

$$\frac{\partial \Pi}{\partial \lambda_i} = f\left(\frac{\partial P}{\partial Q}\frac{\partial Q}{\partial \lambda_i}Q + \frac{\partial Q}{\partial \lambda_i}P\right) - \kappa_{\lambda_i}(\lambda_i,\lambda_j) = fP\left(1+\varepsilon_{P,Q}\right)\frac{\partial Q}{\partial \lambda_i} - \kappa_{\lambda_i}(\lambda_i,\lambda_j), \tag{19}$$

where $\varepsilon_{P,Q} = \frac{\partial P}{\partial Q}\frac{Q}{P} < 0$ is the inverse of the price-elasticity of market quantity and $\kappa_{\lambda_i}(\lambda_i,\lambda_j) < 0$, because higher visibility of product j through recommendation is achieved by lowering λ_i.

Generally, the sign of the first-order condition depends on the sign of $\frac{\partial Q}{\partial \lambda_i}$ and on the magnitude of $\varepsilon_{P,Q}$. Using equations (3) and (9), we can specify the term $(1+\varepsilon_{P,Q})$ to arrive at

$$1+\varepsilon_{P,Q} = \frac{C(\lambda_i\phi_i+\lambda_j\phi_j)g\left(v_H^*\right) - (P-2C)\left(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j\right)g\left(v_L^*\right)}{P[(\lambda_i\phi_i+\lambda_j\phi_j)g\left(v_H^*\right) + (1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)]}. \tag{20}$$

From equation (20), it becomes clear that the size of sellers' marginal production costs qualitatively affects the platform's recommendation policy. Looking at the extreme cases, we can alredy derive several insights for the platform's optimal recommendation policy.

First, if $C = 0$, then the term $1+\varepsilon_{P,Q}$ is unambiguously negative. In this case, the platform would only want to increase consumers' exposure to a substitute product (reduce λ_i) if $\frac{\partial Q}{\partial \lambda_i} > 0$, which according to Proposition 1 occurs when demand is strongly log-convex. Instead, if demand is log-concave or only mildly log-convex, the platform will optimally not recommend a substitute product, i.e., set $\lambda_i = 1$.

Second, if $2C > P$, then the term $1+\varepsilon_{P,Q}$ is unambiguously positive. Hence, the platform would only want to increase consumers' exposure to a substitute product if $\frac{\partial Q}{\partial \lambda_i} < 0$, i.e., when demand is log-concave or only mildly log-convex. Instead, if demand is strongly log-convex, the platform will optimally not recommend any substitute product, i.e., set $\lambda_i = 1$.

If $P > 2C > 0$, the analysis becomes more involved because an increase in consumers' exposure to recommendations of a substitute product (a decrease in λ_i) can imply that the term $1 + \varepsilon_{P,Q}$ changes its sign. Hence, before continuing diving into the platform's optimal recommendation policy, we first introduce the following Lemma:

Lemma 1. *If $P > 2C > 0$, there are parameter constellations of ϕ_0, ϕ_i, ϕ_j and C such that there exists $\hat{\lambda}_i < 1$, where $1 + \varepsilon_{P,Q} \geq 0$ if and only if $\lambda_i \geq \hat{\lambda}_i$.*

Proof. See Appendix A.5 □

With the help of Lemma 1, we can now summarize the platform's optimal recommendation policy. We focus first on the platform's incentives when demand is log-concave or mildly log-convex:

Proposition 5. *If market demand is log-concave or mildly log-convex, such that $\frac{\partial Q}{\partial \lambda_i} < 0$, then the platform will*

(i) recommend a substitute product if either marginal production costs are sufficiently high ($P < 2C$) or they are of intermediate size ($P > 2C > 0$) and $\hat{\lambda}_i < 1$,

(ii) not recommend a substitute product if either marginal production costs are negligible ($C = 0$) or they are of intermediate size ($P > 2C > 0$) and $\hat{\lambda}_i \geq 1$.

Proof. See Appendix A.6 □

To understand the broader implications, we contrast the results of Propositions 2 and 5 in the context of specific markets. First, Proposition 5 applies to situation in which $\frac{\partial Q}{\partial \lambda_i} < 0$. Based on our discussion following Proposition 2, log-concave demand structures are typically found in short-tail, mature and mass markets. Second, these markets are typically characterized by low-to-intermediate marginal production costs due to economics of scale, standardization and automated production techniques. However, there are examples of market segments with high marginal product costs like luxury goods, high-end electronics and performance cars. Third, consumer arrival patterns in such markets are usually shaped by the high visibility and recognition of a small number of popular products due to strong brand awareness and frequent exposure through external channels such as advertising, social media, and search engines. As a result, a large share of consumers arrive having already identified multiple relevant options, leading to a high share of consumers visiting more than one seller's product page. Some consumers, due to idiosyncratic preferences or limited search effort, may still arrive on only one page, though this group is arguably relatively small.

By part (i) of Proposition 5 the platform has an incentive to recommend substitute products in high-cost market segments. However, in low-to-intermediate cost market segments, due to the pattern of consumer arrivals, part (ii) of Proposition 5 implies no incentive to recommend a substitute product. Because by Proposition 2 consumers generally benefit from recommendations of substitute products in short-tail, mature and mass markets, there is a misalignment of interests between the platform and consumers in low-to-intermediate cost segments.

We discuss now the platform's optimal recommendation policy when demand structures are strongly log-convex. We summarize the results in the following proposition:

Proposition 6. *If market demand is strongly log-convex, such that* $\frac{\partial Q}{\partial \lambda_i} > 0$*, then the platform will*

(i) recommend a substitute product if either marginal production costs are negligible ($C = 0$) *or they are of intermediate size* ($P > 2C > 0$) *and* $\hat{\lambda}_i < 1$*, but sufficiently high,*

(ii) not recommend a substitute product if either marginal production costs are sufficiently high ($P < 2C$) *or they are of intermediate size* ($P > 2C > 0$) *and either* $\hat{\lambda}_i \geq 1$ *or* $\hat{\lambda}_i < 1$ *but not sufficiently high.*

Proof. See Appendix A.6 □

As discussed following Proposition 2, strongly log-convex demand structures, where $\frac{\partial Q}{\partial \lambda_i} > 0$, are typically found in long-tail, young and niche markets. Moreover, long-tail markets typically arise because low or negligible inventory and distribution costs make it economically viable to offer niche or low-demand products. For this reason, they are often dominated by digital goods, such as music, e-books, apps, software, podcasts, or educational content, where marginal production and distribution costs are typically zero. By part of (i) Proposition 6, the platform has an incentive to recommend a substitute product under these conditions. This result validates the existence of the previously mentioned paradox because Proposition 2 shows that in long-tail, young and niche markets consumers prefer the platform to not provide recommendations of a substitute product despite the common notion that recommender systems are particularly beneficial in such markets due to costly search for alternative products.

3 Conclusion

This study investigates the nuanced role of recommender systems in markets characterized by product uncertainty and consumers being incompletely aware of alternative options. By extending the standard Cournot framework, we show that the effects of substitute product recommendations depend critically on market characteristics. In short-tail, mature, and mass markets, where consumer preferences are more concentrated and the informational value of recommendations is limited, recommendations tend to enhance consumer surplus by intensifying competition, but the platform lacks the incentives to provide them. In contrast, the platform has an incentive to provide recommendations in long-tail, young, and niche markets. The common perception is that recommendations are most needed in these markets because consumers face the greatest challenges in discovering relevant alternatives due to sparse information, low product visibility, and limited prior knowledge. However, our results emphasize the need for a more nuanced perspective on the benefits of recommender systems in such markets. We show that it is exactly in long-tail, young, and niche markets where recommendations are harmful for consumers highlighting a fundamental paradox.

These results underscore that the welfare impact of recommender systems is highly context-dependent, necessitating a more nuanced perspective. Their role cannot be understood solely in terms of concerns about algorithmic bias and the market frictions that their core functions, such as preference prediction, filtering, personalization, facilitation, and matchmaking, aim to address. Instead, dimensions that have been less explored, such as product uncertainty, must also be considered to fully understand when recommender systems exacerbate inefficiencies. This is crucial for ensuring that platform design choices and policy interventions are effective and well-targeted.

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A Appendix

A.1 Derivation of the market equilibrium

The profit function of firm i reads

$$\pi_i = [(1-f)P - c] \cdot q_i.$$

The first-order condition implies that

$$\frac{\partial \pi_i}{\partial q_i} = [(1-f)P - c] + (1-f)\frac{\partial P}{\partial q_i} q_i = 0$$

where $C = \frac{c}{1-f}$. From Equations (4) and (5), we know that

$$q_i = q_i^E + q_i^C = \lambda_i \phi_i \left[1 - G\left(v_H^*\right)\right] + \left(1 - \phi_0 - \lambda_i \phi_i - \lambda_j \phi_j\right)\left[1 - G\left(v_L^*\right)\right] - q_j^C. \tag{21}$$

Totally differentiation delivers

$$\frac{dP}{dq_i} = -\frac{1}{\lambda_i \phi_i g\left(v_H^*\right) + (1 - \phi_0 - \lambda_i \phi_i - \lambda_j \phi_j) g\left(v_L^*\right)}. \tag{22}$$

Using $\frac{dP}{dq_i}$ and the first-order condition delivers

$$q_i^* = (P - C)[\lambda_i \phi_i g\left(v_H^*\right) + (1 - \phi_0 - \lambda_i \phi_i - \lambda_j \phi_j) g\left(v_L^*\right)]$$

Then, because $Q = q_i + q_j$, we have

$$Q^* = (P - C)\left[(\lambda_i \phi_i + \lambda_j \phi_j) g\left(v_H^*\right) + 2(1 - \phi_0 - \lambda_i \phi_i - \lambda_j \phi_j) g\left(v_L^*\right)\right].$$

By totally differentiating the equation above, we can derive how market quantity is affected by the platform's recommendation policy which reads

$$\begin{aligned}
dQ^* &= \left[(\lambda_i\phi_i+\lambda_j\phi_j)g\left(v_H^*\right)+2(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\right]\frac{\partial P}{\partial Q}dQ \\
&+ \left(P-C\right)\left[(\lambda_i\phi_i+\lambda_j\phi_j)g'\left(v_H^*\right)+2(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g'\left(v_L^*\right)\right]\frac{\partial P}{\partial Q}dQ \\
&+ \left(P-C\right)\phi_i\left[g\left(v_H^*\right)-2g\left(v_L^*\right)\right]d\lambda_i \\
&+ \left(P-C\right)\phi_j\left[g\left(v_H^*\right)-2g\left(v_L^*\right)\right]d\lambda_j
\end{aligned}$$

Using equation (3), and rearranging terms, we arrive at

$$\begin{aligned}
\frac{dQ}{d\lambda_i} &= \frac{\left(P-C\right)\left[(\lambda_i\phi_i+\lambda_j\phi_j)g\left(v_H^*\right)+(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\right]\phi_i\left[g\left(v_H^*\right)-2g\left(v_L^*\right)\right]}{2(\lambda_i\phi_i+\lambda_j\phi_j)g\left(v_H^*\right)\left[1+\frac{(P-C)}{2}\frac{g'\left(v_H^*\right)}{g\left(v_H^*\right)}\right]+3(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\left[1+\frac{2(P-C)}{3}\frac{g'\left(v_L^*\right)}{g\left(v_L^*\right)}\right]}, \\
\frac{dQ}{d\lambda_j} &= \frac{\left(P-C\right)\left[(\lambda_i\phi_i+\lambda_j\phi_j)g\left(v_H^*\right)+(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\right]\phi_j\left[g\left(v_H^*\right)-2g\left(v_L^*\right)\right]}{2(\lambda_i\phi_i+\lambda_j\phi_j)g\left(v_H^*\right)\left[1+\frac{(P-C)}{2}\frac{g'\left(v_H^*\right)}{g\left(v_H^*\right)}\right]+3(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\left[1+\frac{2(P-C)}{3}\frac{g'\left(v_L^*\right)}{g\left(v_L^*\right)}\right]}.
\end{aligned}$$

Similarly, totally differentiating the equation for q_i^*, we can derive how seller i's quantity is affected by the platform's recommendation policy which reads

$$\begin{aligned}
dq_i &= \left[\lambda_i\phi_i g\left(v_H^*\right)+(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\right]\frac{\partial P}{\partial q_i}dq_i \\
&+ \left(P-C\right)\left[\lambda_i\phi_i g'\left(v_H^*\right)+(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g'\left(v_L^*\right)\right]\frac{\partial P}{\partial q_i}dq_i \\
&+ \left(P-C\right)\phi_i\left[g\left(v_H^*\right)-g\left(v_L^*\right)\right]d\lambda_i \\
&- (P-C)\phi_j g\left(v_L^*\right)d\lambda_j.
\end{aligned}$$

Using the equation for $\frac{\partial P}{\partial q_i}$, and rearranging terms, we arrive at

$$\begin{aligned}
\frac{dq_i}{d\lambda_i} &= \frac{\left(P-C\right)\phi_i\left[\lambda_i\phi_i g\left(v_H^*\right)+(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\right]\left[g\left(v_H^*\right)-g\left(v_L^*\right)\right]}{2\lambda_i\phi_i g\left(v_H^*\right)\left[1+\frac{(P-C)}{2}\frac{g'\left(v_H^*\right)}{g\left(v_H^*\right)}\right]+2(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\left[1+\frac{(P-C)}{2}\frac{g'\left(v_L^*\right)}{g\left(v_L^*\right)}\right]}, \\
\frac{dq_i}{d\lambda_j} &= -\frac{\left(P-C\right)\phi_j\left[\lambda_i\phi_i g\left(v_H^*\right)+(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\right]g\left(v_L^*\right)}{2\lambda_i\phi_i g\left(v_H^*\right)\left[1+\frac{(P-C)}{2}\frac{g'\left(v_H^*\right)}{g\left(v_H^*\right)}\right]+2(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\left[1+\frac{(P-C)}{2}\frac{g'\left(v_L^*\right)}{g\left(v_L^*\right)}\right]}.
\end{aligned}$$

A.2 Proof of Proposition 1

From equation (10), we can infer two statements. First, if $g(v)$ is log-convex, we know that $\frac{g'(v)}{g(v)} > 0$, which implies that $g(v_H^*) \geq g(v_L^*)$ because $v_H^* \geq v_L^*$. Whether $2g(v_L^*)$ is greater or smaller than $g(v_H^*)$ depends on how log-convex $g(v)$ is. If $g(v)$ is strongly log-convex, i.e., $\frac{g'(v)}{g(v)} > \frac{\log 2}{\Delta}$, we get that $2g(v_L^*) < g(v_H^*)$, which means that $\frac{dQ}{d\lambda_i} > 0$.[16] Second, if $g(v)$ is only mildly log-convex, i.e., $\frac{\log 2}{\Delta} > \frac{g'(v)}{g(v)} \geq 0$, or mildly log-concave as defined by Assumption 1, we get that $2g(v_L^*) > g(v_H^*)$ and therefore $\frac{dQ}{d\lambda_i} < 0$.

A.3 Proof of Proposition 3

For easier reference, we state the effect of a change in λ_i on seller i's profit again:

$$\begin{aligned}
\frac{\partial \pi_i}{\partial \lambda_i} &= (1-f)\,(P-C)\,\phi_i q_i^* \left[\frac{g\left(v_H^*\right)-g\left(v_L^*\right)}{\Omega_1} - \frac{g\left(v_H^*\right)-2g\left(v_L^*\right)}{\Omega_2}\right], \\
\Omega_1 &= 2\lambda_i\phi_i g\left(v_H^*\right)\left[1+\frac{(P-C)}{2}\frac{g'\left(v_H^*\right)}{g\left(v_H^*\right)}\right] + 2(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\left[1+\frac{(P-C)}{2}\frac{g'\left(v_L^*\right)}{g\left(v_L^*\right)}\right] \\
\Omega_2 &= 2(\lambda_i\phi_i+\lambda_j\phi_j)g\left(v_H^*\right)\left[1+\frac{P-C}{2}\frac{g'\left(v_H^*\right)}{g\left(v_H^*\right)}\right] + 3(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g\left(v_L^*\right)\left[1+\frac{2\,(P-C)}{3}\frac{g'\left(v_L^*\right)}{g\left(v_L^*\right)}\right]
\end{aligned}$$

First, if demand is log-convex, we know that $g(v_H^*) > g(v_L^*)$. As $\Omega_2 > \Omega_1$, the first effect in $\frac{\partial \pi_i}{\partial \lambda_i}$ always dominates which means that $\frac{\partial \pi_i}{\partial \lambda_i} > 0$, i.e., recommendations of the substitute product j is harmful for seller i. Second, if the informational benefit of the recommender system is negligible, i.e., $\Delta = 0$, then we immediately see that $\frac{\partial \pi_i}{\partial \lambda_i}|_{\Delta=0} > 0$. Third, based on the previous results, it is only possible for recommendations of the substitute product j to be beneficial for seller i if demand is log-concave, i.e., when $g(v_L^*) > g(v_H^*)$, because only in this case is the term $\frac{g(v_H^*)-g(v_L^*)}{\Omega_1}$ negative. As the second term $\frac{g(v_H^*)-2g(v_L^*)}{\Omega_2}$ is positive, the first term needs to be sufficiently large for it to dominate. This will be the case if $\lambda_i\phi_i$ sufficiently

[16] The threshold can be derived as follows: We start by taking the logarithm of both sides of the inequality $g(v_H^*) > 2g(v_H^* - \Delta)$, which implies $\log(g(v_H^*)) > \log(2g(v_H^* - \Delta))$, i.e., $\log(g(v_H^*)) - \log(g(v_H^* - \Delta)) > \log 2$. We can express the difference of logs as $\log(g(v_H^*)) - \log(g(v_H^* - \Delta)) = \int_{v_H^*-\Delta}^{v_H^*} \frac{g'(t)}{g(t)} dt$. Plugging into the previous inequality yields $\int_{v_H^*-\Delta}^{v_H^*} \frac{g'(t)}{g(t)} dt > \log 2$, which after dividing both sides by Δ, gives a sufficient condition for $\frac{g'(v)}{g(v)}$, i.e., $\frac{g'(v)}{g(v)} \geq \frac{1}{\Delta}\int_{v_H^*-\Delta}^{v_H^*} \frac{g'(t)}{g(t)} dt > \frac{\log 2}{\Delta}$.

low and $\lambda_j\phi_j$ sufficiently high. As $\lambda_i\phi_i \to 0$ and $\lambda_j\phi_j \to 1-\phi_0$, we know that $\Omega_1 \to \infty$, which means that the first effect becomes very large and will dominate.

A.4 Proof of Proposition 4

For easier reference, we state the effect of a change in λ_j on seller i's profit again:

$$\begin{aligned}
\frac{\partial \pi_i}{\partial \lambda_i} &= -(1-f)(P-C)\phi_j q_i^* \left[\frac{g(v_L^*)}{\Omega_1} + \frac{g(v_H^*) - 2g(v_L^*)}{\Omega_2}\right], \\
\Omega_1 &= 2\lambda_i\phi_i g(v_H^*)\left[1 + \frac{(P-C)}{2}\frac{g'(v_H^*)}{g(v_H^*)}\right] + 2(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g(v_L^*)\left[1+\frac{(P-C)}{2}\frac{g'(v_L^*)}{g(v_L^*)}\right] \\
\Omega_2 &= 2(\lambda_i\phi_i+\lambda_j\phi_j)g(v_H^*)\left[1+\frac{P-C}{2}\frac{g'(v_H^*)}{g(v_H^*)}\right] + 3(1-\phi_0-\lambda_i\phi_i-\lambda_j\phi_j)g(v_L^*)\left[1+\frac{2(P-C)}{3}\frac{g'(v_L^*)}{g(v_L^*)}\right]
\end{aligned}$$

First, if demand is log-convex, we know that $g(v_H^*) > g(v_L^*)$. Then, we can immediately see that $\frac{\partial \pi_i}{\partial \lambda_j} < 0$, i.e., recommendations of the substitute product i is beneficial for seller i. Second, if the informational benefit of the recommender system is negligible, i.e., $\Delta = 0$, then $\frac{\partial \pi_i}{\partial \lambda_i}|_{\Delta=0} < 0$ because $\Omega_2 > \Omega_1$. Third, based on the previous results, it is only possible for recommendations of the substitute product i to be harmful for seller i if demand is log-concave, i.e., when $g(v_L^*) > g(v_H^*)$, because only in this case is the second term $\frac{g(v_H^*)-2g(v_L^*)}{\Omega_2}$ negative. For this term to dominate seller j needs a sufficiently large visibility disadvantage. This will be the case if $\lambda_j\phi_j$ is sufficiently low while $\lambda_i\phi_i$ sufficiently high. As $\lambda_j\phi_j \to 0$ and $\lambda_i\phi_i \to 1-\phi_0$, we know that $\Omega_2 \to \Omega_1$, which means that the second term becomes larger than the first term.

A.5 Proof of Lemma 1

If $P > 2C > 0$, then we know that the sign of equation (20) can be ambiguous. To prove Lemma 1, we first highlight that the effect of ϕ_0, ϕ_i, ϕ_j and C on $1+\varepsilon_{P,Q}$ is unambiguous, i.e., $\frac{\partial(1+\varepsilon_{P,Q})}{\partial C} > 0$, $\frac{\partial(1+\varepsilon_{P,Q})}{\partial \phi_0} > 0$, $\frac{\partial(1+\varepsilon_{P,Q})}{\partial \phi_i} > 0$ and $\frac{\partial(1+\varepsilon_{P,Q})}{\partial \phi_j} > 0$. Second, there exist levels of ϕ_0, ϕ_i, ϕ_j and C for which $1+\varepsilon_{P,Q}$ is unambiguously positive or negative. For example, if

$\phi_i \to 0$ and $\phi_j \to 0$, then $1+\varepsilon_{P,Q} < 0$, whereas if $1-\phi_0 \to 1-\lambda_i\phi_i-\lambda_j\phi_j$, then $1+\varepsilon_{P,Q} > 0$. Similarly, given that for $C \geq 2P$, we have $1+\varepsilon_{P,Q} \geq 0$, and for $C = 0$, we have $1+\varepsilon_{P,Q} < 0$, there exists $\tilde{C}$ for which $1+\varepsilon_{P,Q} = 0$, i.e., $\hat{\lambda}_1 = 1$. Thus, the appropriate combination of these properties allows to generate a situation where $\hat{\lambda}_i < 1$ exists.

A.6 Proof of Propositions 5 and 6

Using equation (20) in (19), we can evaluate the first-order condition at $\lambda_i = 1$ to analyze whether the platform has an incentive to improve visibility of a substitute product, which reads

$$\frac{\partial \Pi}{\partial \lambda_i}|_{\lambda_i=1} = f\frac{C(\phi_i+\lambda_j\phi_j)g\left(v_H^*\right) - (P-2C)\left(1-\phi_0-\phi_i-\lambda_j\phi_j\right)g\left(v_L^*\right)}{(\phi_i+\lambda_j\phi_j)g\left(v_H^*\right) + \left(1-\phi_0-\phi_i-\lambda_j\phi_j\right)g\left(v_L^*\right)}\frac{\partial Q}{\partial \lambda_i} \geq 0,$$

where we used $\kappa_{\lambda_i}(1,\lambda_j) = 0$.

For the case where $P > 2C > 0$, the analysis critically depends on the shape of $g(v)$ because it determines the signs of $1+\varepsilon_{P,Q}$ and $\frac{\partial Q}{\partial \lambda_i}$. There are in total six cases that need to be discuss to fully determine the platform's optimal recommendation policy We discuss each of those cases subsequently:

Case 1: If $\frac{g(v_L^*)}{g(v_H^*)} > \frac{1}{2} > \frac{C(\phi_i+\lambda_j\phi_j)}{(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)}$, then $\frac{\partial Q}{\partial \lambda_i} < 0$ because $g(v_H^*) - 2g(v_L^*) < 0$ and $1+\varepsilon_{P,Q} < 0$, because $(P-2C)\left(1-\phi_0-\phi_i-\lambda_j\phi_j\right)g\left(v_L^*\right) > C(\phi_i+\lambda_j\phi_j)g\left(v_H^*\right)$. By Lemma 1, this means that $\hat{\lambda}_i \geq 0$. Hence, the optimal recommendation policy is to not recommend a substitute product, i.e., set $\lambda_i = 1$.

Case 2: If $\frac{g(v_L^*)}{g(v_H^*)} > \frac{C(\phi_i+\lambda_j\phi_j)}{(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)} > \frac{1}{2}$, then $\frac{\partial Q}{\partial \lambda_i} < 0$ because $g(v_H^*) - 2g(v_L^*) < 0$ and $1+\varepsilon_{P,Q} < 0$ because $(P-2C)\left(1-\phi_0-\phi_i-\lambda_j\phi_j\right)g\left(v_L^*\right) > C(\phi_i+\lambda_j\phi_j)g\left(v_H^*\right)$. Again, by Lemma 1, this means that $\hat{\lambda}_i \geq 1$. Hence, the platform would optimally not recommend a substitute product, i.e., set $\lambda_i = 1$.

Case 3: If $\frac{C(\phi_i+\lambda_j\phi_j)}{(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)} > \frac{g(v_L^*)}{g(v_H^*)} > \frac{1}{2}$, then $\frac{\partial Q}{\partial \lambda_i} < 0$ because $g(v_H^*) - 2g(v_L^*) > 0$ and $1+\varepsilon_{P,Q} > 0$ because $(P-2C)\left(1-\phi_0-\phi_i-\lambda_j\phi_j\right)g\left(v_L^*\right) < C(\phi_i+\lambda_j\phi_j)g\left(v_H^*\right)$, which means that by Lemma 1 we have $\hat{\lambda}_i \geq 1$. Hence, the platform will optimally choose $1 > \lambda_i^*$, i.e., use recommendations.

We summarize the results for the cases where market demand is log-concave, i.e., $\frac{\partial Q}{\partial \lambda_i} < 0$: The platform will optimally not recommend a substitute product if $\hat{\lambda}_i > 1$ (Case 1 and Case 2), and will recommend a substitute product if $\hat{\lambda}_i < 1$ (Case 3).

Case 4: If $\frac{1}{2} > \frac{g(v_L^*)}{g(v_H^*)} \geq \frac{C(\phi_i+\lambda_j\phi_j)}{(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)}$, then $\frac{\partial Q}{\partial \lambda_i} > 0$ because $g(v_H^*) - 2g(v_L^*) > 0$ and $1 + \varepsilon_{P,Q} < 0$ because $(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)g(v_L^*) > C(\phi_i+\lambda_j\phi_j)g(v_H^*)$, which by Lemma 1 means that $\hat{\lambda}_i \geq 1$. As the first-order condition is negative at $\lambda_i = 1$, the platform's optimal policy is to recommend a substitute product, i.e., set $\lambda_i < 1$.

Case 5: If $\frac{1}{2} > \frac{C(\phi_i+\lambda_j\phi_j)}{(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)} > \frac{g(v_L^*)}{g(v_H^*)}$, then $\frac{\partial Q}{\partial \lambda_i} > 0$ because $g(v_H^*) - 2g(v_L^*) > 0$ and $1 + \varepsilon_{P,Q} > 0$ because $(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)g(v_L^*) < C(\phi_i+\lambda_j\phi_j)g(v_H^*)$, which by Lemma 1 means that $\hat{\lambda}_i < 1$. Whether the optimal policy is $\lambda_i = 1$ or $1 > \lambda_i \geq 0$ depends on how high $\hat{\lambda}_i$ is because the first-order condition is positive if $\lambda_i > \hat{\lambda}_i$ while it is negative if $\lambda_i < \hat{\lambda}_i$. A high $\hat{\lambda}_i$ emerges if $(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)g(v_L^*)$ is not too much larger than $C(\phi_i+\lambda_j\phi_j)g(v_H^*)$. There are many constellations that allow such a situation to occur because $\hat{\lambda}_i$ is determined by four exogenous parameters $(\phi_0, \phi_i, \phi_j, C)$ that can be adjusted accordingly. For instance, given ϕ_0, ϕ_i and ϕ_j, there exists a threshold $\tilde{C}$ such that $\left(P-2\tilde{C}\right)(1-\phi_0-\phi_i-\lambda_j\phi_j)g(v_L^*) = \tilde{C}(\phi_i+\lambda_j\phi_j)g(v_H^*)$, i.e., for which $\hat{\lambda}_i = 1$. Then, a marginally higher C implies that $\hat{\lambda}_i$ is marginally lower than 1., which means that the first-order condition turns negative for a large range of values of λ_i. Accordingly, the platform's optimal recommendation policy is set $\lambda_i^* < 1$. A similar logic applies to when $\hat{\lambda}_i$ is not sufficiently high, which means that the platform's optimal recommendation policy is to set $\lambda_i^* = 1$.

Case 6: If $\frac{C(\phi_i+\lambda_j\phi_j)}{(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)} > \frac{1}{2} > \frac{g(v_L^*)}{g(v_H^*)}$, then $\frac{\partial Q}{\partial \lambda_i} > 0$ because $g(v_H^*) - 2g(v_L^*) > 0$ and $1 + \varepsilon_{P,Q} > 0$ because $(P-2C)(1-\phi_0-\phi_i-\lambda_j\phi_j)g(v_L^*) < C(\phi_i+\lambda_j\phi_j)g(v_H^*)$, which by Lemma 1 means that $\hat{\lambda}_i < 1$. The setting in case 6 is the same as in case 5, which means that the same analysis applies.