Competing for Recommendations: The Strategic Impact of Personalized Product Recommendations in Online Marketplaces

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Abstract

This paper studies the impact of an online marketplace's personalized product recommendations and its consumer profiling accuracy on third-party sellers' competition and the market outcomes. Sellers strategically adjust prices to compete for the marketplace's recommendations depending on the latter's recommendation system. When a profit-oriented marketplace recommends products based on the expected profits they generate, as its profiling accuracy increases, the equilibrium price first decreases and then increases. Interestingly, the marketplace's profits may decrease despite its more accurate predictions about consumer preferences. These results are driven by the interaction of three incentives of competing sellers: to win more recommendations from the marketplace, to extract more surplus from high-fit consumers, and to compete for consumers who can find products without recommendations. We also find that the marketplace can improve its profit by excluding pricing information in its recommendation decisions to prevent sellers' recommendation competition, whereas regulations that bar recommendations from considering profit margin information can lead to higher prices and thus harm consumers. Alternatively, when a consumer-oriented marketplace recommends products based on consumer surplus, the main features of recommendation competition persist, and the equilibrium price will be lower in comparison. Finally, various extensions demonstrate the robustness of these results.

Key words: online marketplace, personalization, recommendation system, platform bias, retail platform, platform regulation, search engine optimization

1. Introduction

Recent development of AI-based marketing analytics has given online marketplaces unprecedented powers to generate accurate profiles and personalize product recommendations for each individual consumer. Marketplaces recommend products on websites and through text messages, emails, and mobile push notifications (See Figure A1 in the Online Appendix for examples), helping consumers find products they may not have found otherwise. Personalized recommendation systems have become one of the major profit generators of many online marketplaces, contributing to 35% of transactions on Amazon and 40% of App installs on Google Play, and increasing conversion rates by 20% on Taobao.[1] Field experiments have repeatedly found that personalized recommendation systems can significantly increase firms' profits (Dias et al. 2008; Jannach and Hegelich 2009; Kumar and Hosanagar 2019; Shani, Heckerman, and Brafman 2005).

Many recommendation systems used by online marketplaces consider the profit implications of their recommendations—they prioritize recommending products that lead to the highest expected commission for each recommendation. Since the commissions of most marketplaces are a percentage of product prices (typically 15% on Amazon, 10% on eBay, and 5% on T-mall/Taobao), such profit-oriented recommendation systems may recommend to consumers with more expensive products that yield higher commissions, even if consumers prefer them less than cheaper alternatives. For example, Amazon's personalized recommendation emails will recommend the products that maximize the expected revenue-per-email-sent (Mangalindan 2012), and its personalized search rankings will put forward products that generate higher profits even though these products may not be objectively the best for consumers (Mattioli 2019). Taobao prioritizes recommending products with medium prices, which have balanced conversion rates and per-unit commissions; for instance, the prioritized price range is 220-280 RMB for men's casual suits.[2] Consequently, since product prices will influence the recommendation outcomes, third-party sellers have incentives to strategically adjust their prices to *compete for recommendations*. Anecdotes suggest that third-party sellers realize that their prices can influence the marketplace's recommendations. For example, a

[1] https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-keep-up-with-consumers, https://developers.google.com/machine-learning/recommendation/overview, https://insideretail.asia/2017/06/07/how-alibaba-uses-artificial-intelligence-to-change-the-way-we-shop/
[2] https://kknews.cc/news/6aekz9l.html.

third-party seller on Amazon conjectured that its product appeared much later in search results after a drop in its price because the product would not generate enough commissions for Amazon.[3] Online guides for Amazon sellers have also emphasized price optimization in winning more recommendations to more consumers.[4] Clearly, the sellers' recommendation competition will in turn affect the marketplace's profit. However, extant research on personalized product recommendations has either assumed that the marketplace's recommendation outcomes are independent of product prices, which neglects the marketplaces' profit orientations, or has assumed exogenous product prices, which ignores the sellers' strategic responses to the marketplace's recommendation system. Neither has the previous literature analyzed how changes in the marketplace's consumer profiling accuracy affect different stakeholders in the marketplace.

Given the strategic importance of sellers' pricing decisions and the gap in the existing literature, our paper seeks to address the following research questions. (1) How will the marketplace's recommendation system influence the competition between third-party sellers, and subsequently the payoffs of the marketplace, third-party sellers, and consumers? (2) If the sellers' competition for recommendation can reduce the marketplace's profit, how and when should the marketplace adopt alternative recommendation systems to prevent recommendation competition? (3) How will the marketplace's ability to predict consumers' preferences change the market outcome? Can the marketplace over-target its customers? (4) How will the answers to the questions above change if the marketplace has a consumer-surplus orientation instead of a profit orientation?

To address these research questions, this paper develops an analytical framework in which two third-party sellers offer horizontally differentiated products in an online marketplace and simultaneously set their prices. The marketplace charges the sellers a percentage commission and recommends one and only one product to each of its customers. Different consumers, based on the marketplace's knowledge about their preferences about the two products, can receive different product recommendations. For each consumer, the marketplace receives a noisy signal about her preferences for the two products, and the signal's precision reflects the marketplace's consumer profiling accuracy. In addition to their preferences about the products,

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[3] https://sellercentral.amazon.com/forums/t/amazon-says-lower-your-prices-amazon-does-stops-showing-your-products-in-search-results-because-they-dont-generate-enough-fees/514575
[4] Please see https://sellics.com/blog-amazon-seo/ for an example.

consumers also differ in their information about the products' existence. Informed consumers know both products' existence even without product recommendations (or will find both products regardless of which product is recommended to them), so their consideration set will contain both products. By contrast, uninformed consumers will know a product's existence only via the marketplace's recommendation, so their consideration set will contain only the recommended product but not the other. To capture the marketplace's profit orientation in its recommendation system, we start by examining a marketplace whose objective is to maximize its commission profit, and accordingly considering a profit-based recommendation system. Under such a system, the marketplace, based on each consumer's preference signal and the product prices, will recommend her the product that leads to the highest expected profit (commission) for this recommendation. In addition, we also consider a *price-neutral* recommendation system whose recommendation outcomes will be independent of prices and be solely based on the signals about the consumers' preferences, so the sellers will not strategically alter their prices to compete for recommendations. Analyzing this price-neutral system helps us delineate how recommendation competition influences the market outcomes and when the marketplace's recommendations should ignore product prices to prevent recommendation competition, which we will elaborate on later.

In reality, in addition to the immediate profit generated from each recommendation, marketplaces may also care about its goodwill and customer satisfaction, which positively contributes to its long-term profitability (For succinctness, we simply use "profit" to refer to the "short-term profit" throughout the paper.). To this end, we also consider a consumer-oriented marketplace whose objective is to maximize consumer surplus, which is a proxy for the marketplace's long-term goal. Accordingly, we analyze a *consumer-surplus-based* recommendation system, whose recommendation maximizes the expected consumer surplus from this recommendation, and examine the impact of the recommendation's orientation (consumers surplus vs. profitability) on the equilibrium outcome. Lastly, we also examine a general case where the marketplace has dual goals of improving its profit and consumer surplus, and it uses a *dual-goal* recommendation system that simultaneously attends to both goals.

We highlight several main findings. First, a seller has a "recommendation-competition" incentive to set its price to gain the marketplace's recommendations to more consumers. Under the profit-based recommendation system, a seller tends to set its price that leads to a higher marketplace's profit from the marginal consumers, who tend to have a medium valuation for both products, so the recommendation-competition incentive drives the sellers to set a medium price. In addition, the seller also needs to consider two other incentives when setting its price: The “value-exploitation” incentive drives the seller to set a high price because its product tends to be recommended to consumers with better fit, and the “price-undercutting” incentive motivates the seller to choose a low price to compete directly with its rival for the informed consumers, who will consider both sellers’ products. The equilibrium price under the profit-based recommendation system will be jointly determined by these three incentives.

Second, we find that under the profit-based recommendation system, the equilibrium price first decreases and then increases in the marketplace’s consumer profiling accuracy—the precision of the signal on consumer preferences received by the marketplace. As the signal’s accuracy increases, it becomes harder for a seller, by changing its price, to win the marketplace’s recommendation for a consumer whose signal marginally favors the seller’s competitor, so the recommendation-competition incentive becomes weaker. By contrast, a higher signal accuracy strengthens the value-exploitation incentive because the recommendation system can better match sellers with high-fit consumers. In addition, since recommendations do not directly influence informed consumers, so the signal accuracy will not affect the price-undercutting incentive. Hence, as the profiling accuracy increases, the sellers’ dominant pricing incentive changes from recommendation competition (setting a medium price) to price undercutting (setting a low price), and then to value exploitation (setting a high price). Furthermore, we find that an increase in the profiling accuracy can backfire on the marketplace’s profit. Because the marketplace’s profit is proportional to the total revenue of both sellers, the marketplace will prefer a seller to set a relatively high price to avoid encroaching the other seller’s revenue. Hence, a higher profiling accuracy, when significantly reducing the equilibrium price, can decrease the marketplace’s profit.

Third, we find that the marketplace may increase its profit by adopting the price-neutral recommendation system, which excludes the product price information, compared with using the profit-based system. This result is surprising because if prices were exogenously fixed, the profit-based system would utilize all the profit-relevant information and maximize the marketplace’s total profit by definition. In contrast, when the sellers’ endogenous pricing decisions are considered, the marketplace can prevent the sellers’ recommendation competition by excluding the price information in its recommendations, which can increase the equilibrium prices and the marketplace's profit margin if its profiling accuracy is high. This result challenges a common misconception in the existing literature and in practice—the marketplace could maximize its profit by maximizing the expected profit of each recommendation. Further, this result may help explain the abandonment of incorporating pricing information by some online marketplaces in their recommendation systems after their consumer profiling accuracy has increased. For example, Steam, the leading PC game marketplace, replaced its old recommendation system which favored more expensive games with a new system with significantly high profiling accuracy that disregards any game price information and is entirely based on the potential fit with consumers' preferences.[5]

Fourth, when a marketplace sets out to maximize consumer surplus instead of profits, we show that the sellers still have the three aforementioned pricing incentives and that how the profiling accuracy affects them remains the same. The only difference is that the recommendation-competition incentive now drives the sellers to lower their prices to raise the marginal consumer's surplus. As a result, a higher consumer profiling accuracy, which will strengthen the valuation-exploitation incentive and weaken the recommendation-competition incentive, will increase the equilibrium price and thus the sellers' profits. By contrast, despite the better matching between recommended products and consumers, the improved profiling accuracy can reduce consumer surplus and hence *backfire* on the consumer-oriented marketplace. This finding is analogous to the case of the profit-oriented marketplace, whose payoff can also decrease with the profiling accuracy. Finally, we find that when the marketplace has dual goals of improving its profit and consumer surplus, the sellers still have the same three pricing incentives as before, and the equilibrium outcome is closer to the case of a profit-oriented (resp., consumer-oriented) marketplace when the marketplace weighs its profit (resp., consumer surplus) more in its objective.

Our findings provide several important managerial implications for the marketplaces, the independent sellers, and the regulators. First, a seller in an online marketplace with a profit-based recommendation system needs to be aware that price reduction may lead to fewer recommendations and hence reduce the seller's sales—the demand curve may slope upward. Second, a seller should focus on winning more recommendations with a medium price when the profiling accuracy is low, competing head-to-head with other sellers for informed consumers with a low price when the accuracy is medium, and extracting the

[5] https://steamcommunity.com/games/593110/announcements/detail/1612767708821405787, https://www.techspot.com/news/77689-indie-developers-reportedly-seeing-their-revenue-plummet-due.html

high-valuation consumers' surplus with a high price when the accuracy is high. Third, the marketplace can benefit from exclusion of pricing information in its recommendations if its profiling accuracy is high. Fourth, regardless of whether it is profit-driven or consumer-driven, the marketplace may be harmed by raising profiling accuracy even doing so is costless. This result cautions against a marketplace's "endless" investment in the profiling accuracy. Finally, regulators are recently investigating platforms' practices of profiting with their recommendation systems at the expense of consumers, and most regulations focus on sponsored advertising or platform self-preference (Krämer and Schnurr 2018). By contrast, our paper suggests that a profit-oriented marketplace may also bias its "organic" recommendations towards more expensive products, which can potentially harm consumers. Although this problem may be prevented by a regulation that forbids marketplaces from using any pricing information in their recommendation systems, our analysis shows such regulations can unintendedly lead to higher prices and thus harm consumers.

2. Literature Review

This paper contributes to the literature of personalized recommendation systems. A main research objective of this literature is to develop recommendation algorithms accounting for the product's profit margins for the marketplace, instead of only focusing on conversion metrics such as consumers' purchase likelihood (See Abdollahpouri et al. (2019) for a review.). Besides, several empirical papers, with the assumption of *exogenous* product prices, show that using profit-based recommendation systems can maximize the marketplace's profit (Choi and Mela 2019; Das, Mathieu, and Ricketts 2009; Hinz and Eckert 2010; Shani, Heckerman, and Brafman 2005). By contrast, we show that profit-based recommendations can decrease the marketplace's profit after accounting for the sellers' strategic pricing responses.

Several analytical papers have studied the effects of personalized product recommendations or search rankings (Choudhary and Zhang 2020; Hagiu and Jullien 2011, 2014; Hosanagar, Krishnan, and Ma 2008; Jiang and Zou 2020; Ke, Lin, and Lu 2019; Tam and Ho 2005; Yang and Gao 2017; Yang 2013; Zou and Zhou 2022). Only a few papers have considered that sellers can strategically set prices to influence the recommendation outcomes. Amongst them, Inderst and Ottaviani (2012) consider the setting where third-party sellers can pay a higher per-unit commission to obtain more recommendations, and show that disclosure of such commissions can harm consumers if the sellers differ sufficiently in cost efficiencies. In their model, prices will not affect the marketplace's recommendation decision or a seller's demand in equilibrium. By contrast, in our paper, prices will affect the marketplace's profit, its recommendation decisions, and the seller's demand. Teh and Wright (2020) consider a setting where sellers decide both its price and its per-unit commission paid to the marketplace, which can steer recommendations towards products with higher commissions. They find that recommendation steering will increase the equilibrium commissions and prices only if the commission is freely chosen by the sellers (rather than by the marketplace). By contrast, we study the common e-commerce setting where the commission is determined by the marketplace's commission percentage that applies to all sellers, and we find that recommendation steering may reduce equilibrium prices and will impact the equilibrium outcome even when the marketplace sets the commission. Finally, Zhong (2020) examines a retail marketplace's optimal targeted-search design when the marketplace can commit to a recommendation rule that favors cheaper products. By contrast, our paper studies the setting in which the marketplace cannot make such commitments. Moreover, instead of presuming that the marketplace's recommendations always favor cheaper products, we show that the marketplace's profit-based recommendations will endogenously prioritize products with medium prices, which is consistent with the current practice of major marketplaces such as Taobao. In addition, our paper also studies the effect of consumer profiling accuracy on the market outcomes, while the previous literature either does not capture the profiling accuracy or only considers the extreme case in which the marketplace either perfectly knows the consumers' preferences or knows nothing about them.

3. Model

In this section, we present our assumptions about the online marketplace, the sellers, and the consumers. The running example of this paper is the context where the marketplace recommends consumers with product categories that they may not have been aware of or considered buying before. In the Conclusion section, we explain how our results can be applied to situations where consumers search for a product category or a specific product. Below, we detail our specific assumptions, starting with the sellers.

3.1. Sellers and the Marketplace

Two competing third-party sellers, A and B, sell two substitutable products in the online marketplace. Their marginal production costs are assumed to be zero. The two sellers determine their products' prices, p_A and p_B, respectively, and pay a percentage commission r $(0 < r < 1)$ to the marketplace. Thus, for a unit sale of product $j \in \{A, B\}$, the marketplace's profit is rp_j and seller j's profit is $(1-r)p_j$. The main analysis focuses on the case where the marketplace's commission rate r is exogenous, which is consistent with the current industry practice that commission rates seldom change even if online marketplaces have experienced a lot of changes. For example, the commissions for most product categories have remained 15% on Amazon, 10% on eBay, and 5% on Tmall for years. In Section 6.3, we demonstrate the robustness of our results when the marketplace endogenously decides the commission rate.

The online marketplace profits from every transaction between sellers and consumers on its site. Because its commission from each transaction is a percentage of the transaction price, the marketplace's profit is proportional to the total revenue of the two competing sellers A and B. Based on its recommendation system, the marketplace recommends one and only one product $j \in \{A, B\}$ to each individual consumer. The marketplace does not recommend both products to a consumer, reflecting the recommendation systems' nature of picking only a very small subset from the entire product universe. We will detail how the recommendation system works in the following subsections.

3.2. Consumers

Conditional on knowing both products A and B, consumers are heterogeneous in terms of their horizontal preferences towards these two products. Specifically, consumer i's preference for the two products can be represented by the following utility function à la Singh and Vives (1984):

$$u_i = (\alpha + t_i)q_{iA} + (\alpha - t_i)q_{iB} - \frac{\beta}{2}\left(q_{iA}^2 + q_{iB}^2 + 2zq_{iA}q_{iB}\right) - p_A q_{iA} - p_B q_{iB}. \tag{1}$$

In Equation (1), q_{ij} is consumer i's consumption quantity of product j. α captures consumers' baseline marginal utility from consuming these two products. t_i is this consumer's private information and describes her relative preference between the products—a higher t_i indicates a stronger preference towards product A (i.e., this consumer will buy more A and fewer B). t_i is uniformly distributed between $[-t, t]$, where $t > 0$ captures the level of preference heterogeneity *across* consumers. Finally, $\beta > 0$ captures the consumer's extent of diminishing marginal utility from further consumption, and $z > 0$ measures the level of substitutability between A and B for a *given* consumer (i.e., how a product's price will affect her purchase quantity of the other product). Section 6.1 analyzes an alternative framework where consumers have unit-demand for the products to demonstrate the robustness of our results.

Given the "unlimited" shelf space in the online marketplace and the large number of products it carries, it is essential to model consumers' knowledge about the products' existence. To capture consumers' heterogeneity in their abilities to find relevant products, we assume that there are two distinct consumer segments. The first segment consists of uninformed consumers and is with size $k \in (0,1)$. These consumers know a product's existence only when it is recommended to them by the marketplace, so they will not buy any of the unrecommended product.[6] If product j is recommended to an uninformed consumer i, her preference can be represented by the utility function in Equation (1) with the consumption quantity of the unrecommended product $q_{-j} = 0$, and she will choose her purchase quantity for the recommended product, q_j, to maximize her utility. Hence, if product A is recommended, consumer i's optimal purchase quantity is given by $q_{iA,U} = (\alpha + t_i - p_A)/\beta$ and $q_{iB,U} = 0$, where the subscript U denotes for uninformed consumers, and her surplus is $CS_{iA,U} = \frac{(\alpha - p_A + t_i)^2}{2\beta}$. By contrast, if product B is recommended, her purchase quantity will be $q_{iA,U} = 0$ and $q_{iB,U} = (\alpha - t_i - p_B)/\beta$, and her surplus is $CS_{iB,U} = \frac{(\alpha - p_B - t_i)^2}{2\beta}$.

The second segment consists of informed consumers and is with size $1 - k$. These consumers know both products' existence regardless of the marketplace's recommendation.[7] In other words, the marketplace's recommendation decision does not directly affect their purchase decisions. In reality, k tends to be larger for newer product categories (i.e., in earlier stages of product diffusion) which many consumers are still unaware of. An informed consumer i will choose both $q_{iA,I}$ and $q_{iB,I}$ to maximize her utility, where the subscript I stands for informed consumers. Thus, her optimal purchase quantities of products A and B are

[6] We assume that uninformed consumers will not infer the unrecommended product's existence from merely seeing the recommended product because such inference would require abundant knowledge about the market of the product category (e.g., consumers' valuation distribution), which uninformed consumers typically lack when they just become aware of the product category.

[7] An alternative interpretation of our setup is that all consumers were unaware of any product before receiving recommendations but differ in their probabilities of searching for unrecommended products in the market. Suppose with probability ρ_i consumer i will search for the unrecommended product after receiving the recommendation, and let I be the consumer index set. The equilibrium outcome will be identical to that under our main model with $k = 1 - \int_{i \in I} \rho_i di$. Intuitively, the decisions and the payoffs of the sellers and the marketplace rely only on the expected number of consumers who will consider only the recommended product, instead of how likely each consumer will do so.

$$q_{iA,I} = \frac{1}{\beta}\left[\frac{\alpha(1-z)+t_i(1+z)}{1-z^2} - \frac{1}{1-z^2}p_A + \frac{z}{1-z^2}p_B\right] \tag{2}$$

and

$$q_{iB,I} = \frac{1}{\beta}\left[\frac{\alpha(1-z)-t_i(1+z)}{1-z^2} - \frac{1}{1-z^2}p_B + \frac{z}{1-z^2}p_A\right]. \tag{3}$$

Holding everything else constant, a higher level of competition intensity reflected by a larger z leads to reduced purchase quantities for both products. This consumer's surplus is $CS_{i,I} = \frac{2\left(p_A^2+p_B^2+(2+z)t_i^2+(2-z)\alpha^2-p_B\left((2-z)\alpha-t_i(2+z)\right)-p_A\left((2-z)\alpha+t_i(2+z)\right)\right)-zp_Ap_B}{(4-z^2)\beta}$.

We solve for the symmetric pure-strategy perfect Bayesian equilibrium (PBE), in which both sellers' equilibrium prices are the same.[8] To guarantee the existence of such equilibria, we assume $k > \frac{z^2}{2-z^2}$ and $z < \frac{1}{2}$. To obtain closed-form solutions, we assume that the baseline marginal utility α is large enough relative to t such that in equilibrium, even consumers with the lowest (highest) t_i will buy a positive quantity of product A (product B) conditional on knowing its existence. A sufficient condition for this to hold is $\frac{t}{\alpha} < \frac{1-z}{1+z} \cdot \min\{\frac{1}{2}, \frac{2(2-k(1+z^2))}{4(2-z)-k(3-2z+3z^2)}\}$, which we assume throughout the paper.

3.3. Game Structure

The game has three stages. In the first stage, the two sellers simultaneously set their prices, p_A and p_B, taking into account the marketplace's recommendation system and its commission rate r. In the second stage, after observing the sellers' prices, the recommendation system recommends a product to each individual consumer based on $\hat{t}_i$, the signal of the consumer's relative product preference (t_i). We will elaborate further in the next subsection on the link between a consumer's preference t_i and the signal $\hat{t}_i$ the marketplace draws based on its knowledge about each consumer. In the last stage, consumers make their purchase decisions, and profits are realized for the marketplace and the sellers. This game structure has accounted for three key characteristics in the context of personalized product recommendations. First, it permits the marketplace to personalize recommendations. Second, it allows the sellers' prices to

[8] Our game setting is an imperfect-information one—the marketplace and the sellers do not know consumers' type t_i when making decisions. The PBE guarantees sequential rationality, i.e., the sellers and the marketplace anticipate that each consumer will maximize her utility based on her type t_i and accordingly maximize their respective expected profits. Note that a consumer' payoffs can be pinned down by the product prices, her own t_i, and the product being recommended. Since a consumer observes all the information, she does not need to make any inference in the PBE.

endogenously influence the marketplace's recommendations. Third, it incorporates sellers' strategic pricing decisions in terms of competing with each other and optimally responding to the marketplace's recommendation system. Although important, these three features have not been jointly considered by the extant literature.

3.4. Marketplace's Consumer Profiling

A unique feature of the online marketplace is its ability to track and analyze consumer data and then generate profiles for each individual consumer about her preferences on different products. In this subsection, we detail how the marketplace infers consumers' relative preferences between products A and B. For each consumer, the marketplace receives a noisy signal, $\hat{t}_i$, based on this consumer's actual relative preference for the two products, t_i. To parsimoniously model the marketplace's inference precision of consumer preferences, we assume that for a consumer with t_i, the signal the marketplace draws follows the following pattern: $\hat{t}_i = t_i$ with probability σ, and $\hat{t}_i$ follows the uniform distribution on $[-t, t] \backslash \{t_i\}$ with probability $1 - \sigma$. Formally, the probability of the generated signal $\hat{t}_i$ conditional on the actual t_i is

$$\Pr(\hat{t}_i \leq x | t_i) = \begin{cases} \frac{(x+t)(1-\sigma)}{2t}, \text{if } x < t_i; \\ \sigma + \frac{(x+t)(1-\sigma)}{2t}, \text{if } x \geq t_i \, . \end{cases} \tag{4}$$

One can show that the (unconditional) distribution for $\hat{t}_i$ is also a uniform distribution on $[-t, t]$. By Bayes rule, the marketplace's posterior belief for consumer i's preference t_i conditional on the signal $\hat{t}_i$ is

$$\Pr(t_i \leq x | \hat{t}_i) = \begin{cases} \frac{(x+t)(1-\sigma)}{2t}, \text{if } x < \hat{t}_i; \\ \sigma + \frac{(x+t)(1-\sigma)}{2t}, \text{if } x \geq \hat{t}_i. \end{cases} \tag{5}$$

Based on the marketplace's posterior belief, the expectation of t_i conditional on $\hat{t}_i$ is $E[t_i | \hat{t}_i] = \sigma \hat{t}_i$. The probability $\sigma \in (0,1]$ captures the precision of the marketplace's inference about its consumers' preference t_i. When $\sigma \to 0$, the signal is completely uninformative in the limit, so the marketplace's posterior belief about t_i remains to be its prior—a uniform distribution on $[-t, t]$. When $\sigma = 1$, the signal is perfectly precise, such that with probability one $\hat{t}_i$ is the same as t_i. When $\sigma \in (0,1)$, the marketplace's inference about consumer preference is imperfectly informative. We denote σ as the marketplace's profiling accuracy, which captures the marketplace's technologies of figuring out consumers' exact preferences. Later, we will examine the impact of such technologies with the comparative static analyses on σ.

Because informed consumers will always consider both products regardless of the marketplace's recommendation, without loss of generality, we will focus on the recommendations to uninformed consumers. Given the signal $\hat{t}_i$, the expected purchase quantity of the uninformed consumer i conditional on the marketplace's recommendation is given in Table 1. One can see that if consumer i's signal $\hat{t}_i > 0$, as the marketplace's profiling accuracy σ increases, this consumer is expected to purchase more (less) of product A (B) if it is recommended to her. By contrast, if $\hat{t}_i < 0$, as σ increases, this consumer is expected to purchase less (more) of product A (B) if it is recommended to her.

Table 1 The Marketplace's Posterior Expectation of Consumer i's Purchase Quantity Given $\hat{t}_i$

Product Recommended	$E[q_{iA,U}\|\hat{t}_i]$	$E[q_{iB,U}\|\hat{t}_i]$
Product A	$(\alpha + \sigma\hat{t}_i - p_A)/\beta$	0
Product B	0	$(\alpha - \sigma\hat{t}_i - p_B)/\beta$

4. Analysis: Marketplace with a Profit Orientation

This section considers a profit-oriented marketplace, whose objective is to maximize its profit. This setting reflects many marketplaces' tendencies (e.g., Amazon, Taobao) of recommending products that generate a higher commission profit for each recommendation. First, we will examine the market outcomes under the profit-based and under the price-neutral recommendation systems. Under the profit-based recommendation system, the marketplace will recommend a consumer with the product that maximizes the marketplace's expected profit from this recommendation *given the product prices*. Note that the profit-based recommendation system is defined by its recommendation rule (recommending the product with the highest expected profit), and it does not mean that it would always maximize the marketplace's total profit (and we will later show it will not). By contrast, under the price-neutral recommendation system, the recommendations will be independent of the prices and only depend on each consumer's preference signal

$\hat{t}_i$. For example, Steam's new recommendation system is price-neutral because it ignores product prices and uses only the features of games and consumers (e.g., game gerne, consumer purchase history). Then, we will compare the market outcomes under the two types of recommendation systems. Note that the sellers will adjust their prices to compete for recommendations under the profit-based system, whereas such recommendation competition is absent under the price-neutral system because the prices will not influence recommendation outcomes. Hence, contrasting the market outcomes under the two systems can cleanly delineate how recommendation competition influences sellers' pricing decisions, and when the marketplace should ignore prices in its recommendations to prohibit recommendation competition.

4.1. Price-Neutral Recommendation System (PN)

Under a price-neutral recommendation system (denoted by PN), the recommendation outcomes are independent of the product prices, and the marketplace will recommend a product to a consumer solely based on which product fits this consumer better in expectation. Therefore, it will recommend product A to consumer i if her signal $\hat{t}_i \geq 0$, and will recommend product B if $\hat{t}_i < 0$.

Given the two prices p_A and p_B, product A's demand is given by

$$\begin{aligned} D_A^{PN} &= \underbrace{k \cdot \int_{\mathbf{0}}^{t} E\left[q_{iA,U} \middle| \hat{t}_i\right] \mathrm{d}F_{\hat{t}}(\hat{t}_i)}_{\text{Demand from uninformed consumers}} + \underbrace{(1-k) \cdot \int_{-t}^{t} q_{iA,I} \, \mathrm{d}F_t(t_i)}_{\text{Demand from informed consumers}} \\ &= \frac{1}{\beta} \cdot \left[\frac{k}{2}\left(\alpha - p_A + \frac{\sigma t}{2}\right) + (1-k)\left(\frac{\alpha}{1+z} - \frac{1}{1-z^2} p_A + \frac{z}{1-z^2} p_B\right)\right]. \end{aligned} \tag{6}$$

The first component in this demand function is the expected purchase quantity from the uninformed consumers, who know a product's existence only from recommendations. k is the size of the uninformed segment, and $E\left[q_{iA,U} \middle| \hat{t}_i\right]$ denotes consumer i's expected purchase quantity conditional on $\hat{t}_i$. Note that under the price-neutral recommendation system, since product A is recommended if and only if $\hat{t}_i \geq 0$, its aggregate demand from uninformed consumers is an integration from 0 to t (with respect to $\hat{t}_i$). The second component in Equation (6) is the expected purchase quantity from the informed consumers, whose purchase decisions do not directly depend on product recommendations. $(1-k)$ is the size of this consumer segment, and $\int_{-t}^{t} q_{iA,I} \, \mathrm{d}F_t(t_i)$ is each consumer's expected purchase quantity.

Similarly, product B's demand is given by

$$D_B^{PN} = \frac{1}{\beta} \cdot [\frac{k}{2}\left(\alpha - p_B + \frac{\sigma t}{2}\right) + (1-k)(\frac{\alpha}{1+z} - \frac{1}{1-z^2} p_B + \frac{z}{1-z^2} p_A)]. \quad (7)$$

Maximization of the two sellers' profit functions $(1-r)p_A D_A^{PN}$ and $(1-r)p_B D_B^{PN}$ leads to the following result on the equilibrium pricing. We relegate all proofs to the Online Appendix.

Proposition 1. *Under the price-neutral recommendation system, the equilibrium prices are* $p^{PN*} = \frac{(1-z)(4\alpha - 2k\alpha(1-z) + k(1+z)\sigma t)}{4(2-z-k(1-z+z^2))}$ *for both sellers. This price increases in the marketplace's profiling accuracy* σ.

Proposition 1 shows that under a price-neutral recommendation system, the equilibrium prices will increase with the marketplace's consumer profiling accuracy σ. A seller needs to consider two distinct incentives when setting its price. On the one hand, a seller is motivated to charge a high price because personalized recommendations help put forward this seller's products to uninformed consumers with a better match, and this incentive will be stronger when consumer profiling is more accurate (σ is higher). We label this driving force as the seller's "value-exploitation" incentive. On the other hand, a seller is inclined to choose a low price to directly compete with its rival for the informed consumers, who always consider both substitutable products. We label this as the seller's "price-undercutting" incentive. Its strength is independent of σ because this incentive applies only to informed consumers, who will not be directly influenced by product recommendations. Taken together, the sellers tend to set higher prices when σ increases. Furthermore, in our framework p^{PN*} increases linearly in σ, so the magnitude of the value-exploitation incentive is proportional to σ.

Corollary 1. *Under the price-neutral recommendation system, the profits of the two sellers and the marketplace all increase in the marketplace's profiling accuracy* σ.

Under the price-neutral recommendation system, a better expected match between each seller and its consumers due to a greater σ allows the former to charge a higher price and consequently improves its profits. Furthermore, because the marketplace's total commission is proportional to the total profits of the two sellers, $r(p_A D_A^{PN} + p_B D_B^{PN})$, it is also better off when σ increases.

4.2. Profit-based Recommendation (PB)

Now we examine the profit-based recommendation system (denoted by PB). Unlike the price-neutral system, the profit-based system incorporates the two sellers' pricing information in its algorithm, giving the sellers incentives to compete for recommendations through price adjustment. The literature and the practitioners have largely assumed that the profit-based system's profit orientation will maximize the marketplace's profit. The following result confirms this intuition if the product prices are *exogenously* given.

Result 1. *Given prices* p_A *and* p_B*, among all recommendation systems, the marketplace's profit is the highest under the profit-based recommendation system.*

The following analysis will consider the interesting case in which the sellers endogenously decide their prices. We analyze the game with backward induction, starting with the marketplace's personalized recommendations. Consider an uninformed consumer i with the signal $\hat{t}_i$. If the marketplace recommends product A to this consumer, its expected profit (denoted by Π) from her conditional on her signal $\hat{t}_i$ is $E\left[\Pi_{i,A}\middle|\hat{t}_i\right] = E\left[q_{i,A}\middle|\hat{t}_i\right] \cdot rp_A = \frac{\alpha+\sigma\hat{t}_i-p_A}{\beta} \cdot rp_A$. Similarly, if the marketplace recommends product B to consumer i, its expected profit from her is $E\left[\Pi_{i,B}\middle|\hat{t}_i\right] = \frac{\alpha-\sigma\hat{t}_i-p_B}{\beta} \cdot rp_B$. To facilitate exposition, we define $G(p_A, p_B) = \frac{(p_A-p_B)(p_A+p_B-\alpha)}{p_A+p_B}$. Under the profit-based recommendation system, the marketplace will recommend product A to consumer i if and only if $E\left[\Pi_{i,A}\middle|\hat{t}_i\right] \geq E\left[\Pi_{i,B}\middle|\hat{t}_i\right]$, which translates to $\hat{t}_i \geq \frac{G(p_A,p_B)}{\sigma} \stackrel{\text{def}}{=} \hat{t}_0$; the marketplace will recommend product B to consumer i if and only if $\hat{t}_i < \hat{t}_0$.[9] A lower $\hat{t}_0$ implies that the marketplace will recommend product A to more uninformed consumers and product B to fewer uninformed consumers. Given the importance of the recommendation threshold $\hat{t}_0$ in our analysis, we next characterize its relationship with product prices in the following lemma.

[9] To simplify exposition, throughout the paper, we assume the recommendation threshold $\hat{t}_0 \in (-t, t)$, i.e., both products will be recommended to some uninformed consumers. This condition will hold in any symmetric equilibrium, in which $\hat{t}_0 = 0$. Note that the sellers' demand and profit functions have kinks at $\hat{t}_0 = -t$ and at $\hat{t}_0 = t$. In the appendix, we show that under the conditions $k > \frac{z^2}{2-z^2}$ and $z \leq \frac{1}{2}$, a seller will never set its price such that $\hat{t}_0 \notin (-t, t)$ if the other seller charges the equilibrium price, so it is without loss of rigor to assume $\hat{t}_0 \in (-t, t)$.

Lemma 2. *Under the profit-based recommendation system, the recommendation threshold $\hat{t}_0$ is a U-shaped function of price p_A: As p_A increases, $\hat{t}_0$ first decreases and then increases. By contrast, $\hat{t}_0$ is an inverted U-shaped function in price p_B: As p_B increases, $\hat{t}_0$ first increases and then decreases.*

Because of the symmetry of the two sellers, we focus on explaining how $\hat{t}_0$ changes with seller A's price p_A. Lemma 2 implies that as p_A increases, the marketplace will first recommend product A to more uninformed consumers and then to fewer of them. In other words, the marketplace has an incentive to prioritize recommending products with medium prices. This is because, for an uninformed consumer, the marketplace will recommend her the product that can generate the higher expected commission. For a consumer with the marginal signal ($\hat{t}_i = \hat{t}_0$), an increase in p_A will increase the marketplace's per-unit sale commission but will reduce the expected quantity of product A this consumer purchases. From $\frac{\partial \hat{t}_0}{\partial p_A} = \frac{1}{\sigma}(1 - \frac{2\alpha p_B}{(p_A+p_B)^2})$, we can see that when p_A is relatively low, i.e., $p_A \leq \sqrt{2\alpha p_B} - p_B$, the first effect on the commission dominates the second effect on the sales quantity, so the marketplace is more likely to recommend product A to this marginal consumer. By contrast, when p_A exceeds $\sqrt{2\alpha p_B} - p_B$, further increases in p_A (which is already relatively high) will reduce the marketplace's likelihood of recommending product A. In a symmetric equilibrium with $p_A^* = p_B^* = p^*$, $\frac{\partial \hat{t}_0}{\partial p_A}$ increases in p_A (at $p_A = p^*$) when $p^* > \frac{\alpha}{2}$, and decreases in p_A when $p^* < \frac{\alpha}{2}$. Note that $\alpha/2$ is the exact price that maximizes the marketplace's expected profit for the consumer with a neutral signal, $\hat{t}_i = 0$, who can be considered as the marginal consumer from the sellers' perspective when they compete for the recommendation. Hence, holding everything else constant, in equilibrium a seller is more likely to obtain the marketplace's recommendation for this marginal consumer by slightly adjusting its price closer to $\alpha/2$.

Given the two prices p_A and p_B, product A's demand is given by

$$\begin{aligned} D_A^{PB} = & \underbrace{k \cdot \int_{\hat{t}_0}^{t} E\left[q_{iA,U} \middle| \hat{t}_i\right] \mathrm{d}F_{\hat{t}}(\hat{t}_i)}_{\text{Demand from uninformed consumers}} + \underbrace{(1-k) \cdot \int_{-t}^{t} q_{iA,I} \, \mathrm{d}F_t(t_i)}_{\text{Demand from informed consumers}} \\ & = \frac{k}{2\beta}\left(1 - \frac{G(p_A,p_B)}{t\sigma}\right)\left[\alpha + \frac{t\sigma}{2} - p_A + \frac{G(p_A,p_B)}{2}\right] + \frac{1-k}{\beta}\left[\frac{\alpha}{1+z} - \frac{1}{1-z^2}p_A + \frac{z}{1-z^2}p_B\right]. \end{aligned} \tag{8}$$

Similar to Equation (6), the first component in this demand function is the expected purchase quantity from the uninformed consumers. Notably, the integral reflects that under the profit-based recommendation system, the marketplace will recommend product A if and only if $\hat{t}_i \geq \hat{t}_0$. This is in sharp contrast with the case of the price-neutral recommendation system, under which product A will be recommended to consumers when $\hat{t}_i \geq 0$. The second component in Equation (8) is the expected purchase quantity from the informed consumers, which is the same as the counterpart under the price-neutral system in Equation (6).

Importantly, under the profit-based recommendation system, a seller can strategically adjust its price to influence the recommendation threshold $\hat{t}_0$ and thus its demand. Specifically, a seller tends to set a medium price (closer to $\alpha/2$) so that the marketplace will recommend its product to more consumers. We label this as the sellers' "recommendation-competition" incentive. Note that the recommendation-competition incentive only exists under the profit-based recommendation system but not under the price-neutral system, and that its magnitude, characterized by $|\frac{\partial \hat{t}_0}{\partial p_j}|$, is proportional to $1/\sigma$. In other words, when the marketplace can more precisely infer consumers' preferences, the impact of the seller's price on the recommendation threshold $\hat{t}_0$ will be reduced. Intuitively, when the signal becomes more accurate, the marketplace will have stronger confidence in predicting each consumer's preference. As a result, it becomes more difficult for a seller, by changing its price, to persuade the marketplace to recommend its product to a consumer whose signal marginally favors the other seller.

Similarly, product B's demand is given by

$$D_B^{PB} = \frac{k}{2\beta}\left(1 + \frac{G(p_A, p_B)}{t\sigma}\right)\left[\alpha + \frac{t\sigma}{2} - p_B - \frac{G(p_A, p_B)}{2}\right] + \frac{1-k}{\beta}\left[\frac{\alpha}{1+z} - \frac{1}{1-z^2}p_B + \frac{z}{1-z^2}p_A\right]. \tag{9}$$

Interestingly, Equations (8) and (9) imply that, under the profit-based recommendation system, a higher price can *increase* a seller's demand because the marketplace may recommend the seller's product to more consumers. Hence, when selling through a marketplace with a profit-based recommendation system, a seller should not price too aggressively in order to guarantee that the marketplace can earn sufficient commission by recommending this seller's product. Corollary 2 summarizes the result.

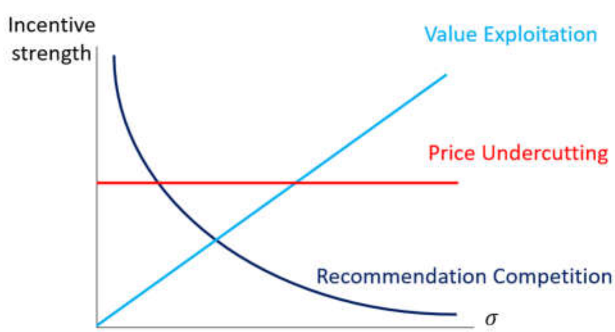
Corollary 2. *Under the profit-based recommendation system, a seller's demand can increase with its price.*

Maximization of the two sellers' profit functions $(1-r)p_A D_A^{PB}$ and $(1-r)p_B D_B^{PB}$ leads to the following proposition about the equilibrium pricing.

Proposition 2. *Under the profit-based recommendation system, the equilibrium price is* $p^{PB*} = \frac{\alpha}{4k(1-z^2)}\left(4\tilde{\sigma}(2-z) + k\big(3(1-z^2) - 4\tilde{\sigma}(1-z+z^2)\big) - \left(\left(4\tilde{\sigma}(2-z) + k\big(3(1-z^2) - 4\tilde{\sigma}(1-z+z^2)\big)\right)^2 - 8k(1-z)(1-z^2)\left(4\tilde{\sigma} + k\big((1+\tilde{\sigma}^2)(1+z) - 2\tilde{\sigma}(1-z)\big)\right)\right)^{\frac{1}{2}}\right)$ *for both sellers, where* $\tilde{\sigma} = t\sigma/\alpha$. *This equilibrium price first decreases in the marketplace's profiling accuracy* σ *when* $0 \leq \sigma \leq \sigma_0$ *and then increases in* σ *when* $\sigma_0 < \sigma \leq 1$.[10]

Proposition 2 reveals a U-shaped relationship between the equilibrium price and the marketplace's profiling accuracy under the profit-based system. As discussed earlier, the strength of the recommendation-competition incentive (setting a medium price) is proportional to $1/\sigma$, the strength of the value-exploitation incentive (setting a high price) is proportional to σ, and the strength of the price-undercutting incentive (setting a low price) is independent to σ. Figure 2 summarizes how the strengths of the sellers' three pricing incentives change with σ. As the consumers' profiling accuracy increases, the sellers' dominant pricing incentive changes from recommendation competition to price undercutting, and finally to value exploitation. Accordingly, the equilibrium price will change from medium to low, and finally to high (See Figure 3 later).

Figure 2 Effects of σ on the Sellers' Pricing Incentives



After analyzing how the marketplace's profiling accuracy influences the equilibrium price, we next discuss how it impacts different participants' profits.

Proposition 3. *With the profit-based recommendation system, the profits of the two sellers and the marketplace can decrease in the marketplace's profiling accuracy* σ. *A sufficient condition for this to*

[10] The threshold σ_0 is defined in the Online Appendix and can exceed one, in which case the equilibrium price always decreases with σ on $(0,1]$.

happen is that the elasticity of the equilibrium price in the profiling accuracy is lower than -1*, i.e.,* $\frac{\partial p^{PB*}/p^{PB*}}{\partial \sigma/\sigma} < -1$.

One may expect that a greater profiling accuracy enabled by more advanced consumer analytics will improve the match between products and consumers and thus increase the marketplace's profits. Corollary 1 has validated this intuition in the case of the price-neutral recommendation system, where sellers do not compete for recommendations. Interestingly, Proposition 3 shows that this lay intuition may not hold under the profit-based recommendation system—a higher profiling accuracy can backfire and reduce the profits of both the marketplace and its sellers. Specifically, this will happen when a higher profiling accuracy significantly reduces the equilibrium price such that the elasticity of the equilibrium price with respect to the profiling accuracy is lower than -1. Intuitively, if an increase in σ significantly weakens the sellers' incentive to compete for the marketplace's recommendation (which can occur when σ is relatively low based on Proposition 2), the price-undercutting incentive will become dominant, leading to lower equilibrium prices and profits for the sellers and for the marketplace.

4.3. Recommendation System Comparison and Consumer Surplus

This subsection analyzes the effect of recommendation competition by comparing the market outcomes under the profit-based system and the price-neutral system. In situations where recommendation competition can reduce the marketplace's profit, the marketplace may want to adopt a price-neutral system to prevent such competition. Proposition 4 compares the equilibrium prices under the two different recommendation systems.

Proposition 4. *There exists* $\bar{\sigma} > 0$ *such that the equilibrium price is* $\frac{\alpha}{2}$ *under both types of recommendation systems when* $\sigma = \bar{\sigma}$*. When* $\sigma < \bar{\sigma}$*, the equilibrium price under the profit-based recommendation system is higher than that under the price-neutral recommendation system, and both are below* $\frac{\alpha}{2}$*, i.e.,* $p^{PN*} < p^{PB*} < \frac{\alpha}{2}$*. When* $\sigma > \bar{\sigma}$*, the price under the price-neutral recommendation system is higher than that under the profit-based system, and both are above* $\frac{\alpha}{2}$*, i.e.,* $\frac{\alpha}{2} < p^{PB*} < p^{PN*}$.

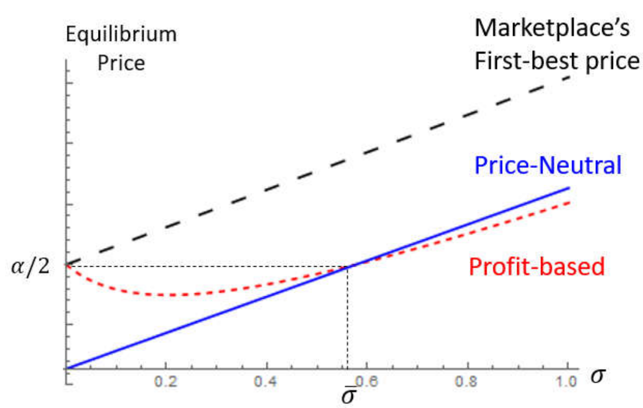
The key difference in the equilibrium prices between the two recommendation systems is that the recommendation-competition incentive, which bends the equilibrium price closer to $\alpha/2$, exists only in the profit-based system but not in the price-neutral system. First, when $\sigma < \bar{\sigma}$, the value-exploitation incentive is weaker than the price-undercutting incentive, and the sellers are inclined to set their prices below $\alpha/2$. The recommendation-competition incentive, uniquely present under the profit-based system, will drive the sellers to raise their prices closer to $\alpha/2$, so the equilibrium price under the profit-based system is higher than that under the price-neutral system. Second, when $\sigma = \bar{\sigma}$, the equilibrium prices will be $\alpha/2$ under both recommendation systems. At this price, the recommendation-competition incentive has been fully satisfied, so it will no longer have any impact in equilibrium. Third, when $\sigma > \bar{\sigma}$, the value-exploitation incentive is stronger than the price-undercutting incentive, and the sellers tend to set their prices above $\alpha/2$. Due to the recommendation-competition incentive under the profit-based system, sellers will drop their prices closer to $\alpha/2$, so the equilibrium price under the price-neutral recommendation system will be higher.

Next, we analyze how recommendation competition affects profits of the marketplace and the sellers. It is useful to first consider the marketplace's first-best price (p^{**})—the optimal price the marketplace would set if it could dictate both sellers' prices. Furthermore, in the Online Appendix, we show that $\max\{p^{PN*}, p^{PB*}\} < p^{**}$, i.e., the marketplace's first-best price is higher than the equilibrium prices under both the price-neutral and the profit-based recommendation systems. Unsurprisingly, if the prices were set by the marketplace rather than independently by the competing sellers, the marketplace would raise the prices to avoid cannibalizing the sales of other products. Figure 3 provides an example of how the consumer profiling accuracy affects the equilibrium prices under the two recommendation systems, and how these prices compare with the marketplace's first-best price. These results together imply that when comparing the two systems, the one with a higher equilibrium price will generate a greater profit for the marketplace. The following proposition formally summarizes how recommendation competition affects the marketplace's and the sellers' profits across the two different recommendation systems.

Proposition 5. *The profits for the marketplace and the sellers under the profit-based recommendation system are lower than their counterparts under the price-neutral recommendation system if and only if* $\sigma \geq \bar{\sigma}$*; otherwise, their profits are higher under the profit-based recommendation system.*

The profit-based recommendation system aims to maximize the marketplace's profit by maximizing the expected profit from each personalized recommendation. As Result 1 suggests, the profit-based system does maximize the marketplace's profit if the prices are exogenous. Counterintuitively, Proposition 5 demonstrates that if the sellers strategically set their prices, the marketplace's profit as well as the two sellers' can be lower under the profit-based system than under the price-neutral system. This outcome occurs when $\sigma \geq \bar{\sigma}$, because in this region p^{PB*} lies further below the marketplace's first-best price (p^{**}) than p^{PN*} does. Intuitively, when the profiling accuracy is high, the marketplace would prefer relatively high prices (higher than $\alpha/2$) to extract the surplus of each seller's high-fit consumers. However, under the profit-based recommendation system, recommendation competition drives the sellers to set prices closer to $\alpha/2$ to compete for the marginal, medium-fit consumers, which in turn lowers the marketplace's profit. In other words, when $\sigma \geq \bar{\sigma}$, the marketplace can earn a higher profit by using a price-neutral system, which ignores the price information and thus eliminates the recommendation competition. This result is consistent with the anecdote that Steam, along with its adoption of a more accurate recommendation system, switched from a profit-based recommendation system to the price-neutral one.

Figure 3 Effect of σ on Equilibrium Prices Under Different Recommendation Systems[11]



We next examine the implications of the marketplace's recommendation system on consumer surplus.

Corollary 3. *(1) Under both recommendation systems, consumers will receive the recommendation for the product that offers higher surplus to them. (2) Consumer surplus is higher under the profit-based recommendation system if and only if $\sigma > \bar{\sigma}$. Otherwise, consumer surplus is higher under the price-neutral recommendation system.*

[11] In this plot, $t = 0.35, \alpha = 1, \beta = 1, k = 0.5$, and $z = 0.1$.

First, under both recommendation systems, in equilibrium the marketplace will recommend an uninformed consumer the product offering higher expected surplus to her, so consumers are not "deceived" by the marketplace to buy the product with lower expected surplus.[12] Second, we find that consumers are better off under the profit-based recommendation system when the marketplace's profiling accuracy is high. This result sheds new light on the recent platform regulations, which tend to require marketplaces to exclude price or profit-margin information in recommendations, because the profit-based recommendation system can recommend products that are more expensive but with poorer fits. However, Corollary 3 suggests that when the marketplace's consumer profiling is relatively accurate, such regulations can actually hurt consumers.

With the growing dominance of a few online marketplaces in e-commerce, regulatory agencies have started questioning their use of customer data and its potential negative impact on consumers. This naturally raises the question on how an improvement of the marketplace's profiling accuracy influences the overall consumer surplus. We answer this question in the following proposition.

Proposition 6. *Consumer surplus increases in the marketplace's profiling accuracy σ under both recommendation systems.*

Proposition 6 shows that regardless of whether the marketplace adopts the price-neutral or the profit-based recommendation system, a higher level of profiling accuracy will benefit consumers. Conventional wisdom might suggest that the more advanced technology by the marketplace allows it to better extract the surplus from consumers. While this effect is clearly present, another driving force cannot be overlooked: A higher σ enables the marketplace to recommend uninformed consumers the products with a better fit. Overall, the impact of better matching outweighs the impact of potentially higher prices from better targeting. This finding cautions antitrust regulators against blanketly limiting marketplaces' access to consumer data. After all, the service of matching consumers with their more preferred alternatives creates values for consumers, so regulations that limit the marketplace's ability to obtain or utilize consumer data (e.g., GDPR, CCPA) can reduce the recommendation accuracy and possibly alleviate seller competition, which will eventually hurt the consumers.

[12] We thank the Associate Editor for suggesting this point.

5. Marketplace with a Consumer Orientation

In Sections 4, the marketplace has a sole objective of maximizing its immediate profit from the recommendations, which allows us to focus on how the marketplace's profit orientation affects the sellers' competition under a recommendation system. In practice, the marketplace may also care about consumers' surplus from its recommendations, which can influence the marketplace's goodwill and long-term profitability (as opposed to its "short-term" profit *directly* from the recommendations). This section studies the sellers' recommendation competition when the marketplace attends to consumer surplus. We first analyze a consumer-oriented marketplace, which cares *only about* consumer surplus, and then compare the equilibrium outcomes under a consumer-oriented marketplace with those under a profit-oriented one. These two cases are two extreme representations of the marketplace's goals to maximize its profit and improve consumer surplus, respectively. Finally, we examine a general case in which the marketplace has dual orientations of improving its profit and consumer surplus.

5.1. Consumer-oriented Marketplace

In this case, the marketplace's objective is to maximize consumer surplus. Accordingly, we consider its consumer-surplus-based recommendation system (denoted as "CB"), which recommends each consumer with the product that maximizes her surplus given the product prices. This is parallel to the earlier discussion of the profit-based recommendation system when the marketplace's sole objective is to maximize its profit. Under the consumer-surplus-based system, an uninformed consumer with signal $\hat{t}_i$ will receive the expected surplus of $E\left[CS_{i,A}\middle|\hat{t}_i\right] = \frac{1}{2\beta}[\sigma(\alpha - p_A + \hat{t}_i)^2 + (1-\sigma)(\frac{t^2}{3} + (\alpha - p_A)^2)]$ if product A is recommended; her expected surplus will be $E\left[CS_{i,B}\middle|\hat{t}_i\right] = \frac{1}{2\beta}[\sigma(\alpha - p_B - \hat{t}_i)^2 + (1-\sigma)(\frac{t^2}{3} + (\alpha - p_B)^2)]$ if product B is recommended. The consumer-surplus-based recommendation system will recommend product A if and only if $E\left[CS_{i,A}\middle|\hat{t}_i\right] > E\left[CS_{i,B}\middle|\hat{t}_i\right]$, which is equivalent to $\hat{t}_i > \hat{t}_{0,CB}(p_A, p_B) \overset{\text{def}}{=} \frac{p_A - p_B}{2\sigma}$. Under this recommendation system, the cheaper a product is, the more consumer surplus it generates, and the more consumers it will be recommended to. This differs from the profit-based system, which tends to recommend a product with a medium price.

Many key features of the sellers' pricing incentives remain the same under the consumer-surplus-based recommendation system as those under the profit-based one. Specifically, under both systems, the sellers have three distinctive pricing incentives—valuation exploitation, price undercutting, and recommendation competition. Note that the first two incentives are independent of the marketplace's recommendation rule, hence they stay exactly the same between the two systems. Furthermore, the magnitudes of the third incentive (recommendation competition), $|\frac{\partial \hat{t}_0}{\partial p_j}|$, are both proportional to $1/\sigma$ under the two systems. The only difference is that under the profit-based system the recommendation-competition incentive motivates the sellers to set medium prices that maximize the marketplace's profit from the marginal consumer, whereas under the consumer-surplus-based system this incentive drives the sellers to lower their prices to increase the marginal consumer's surplus.

The following proposition presents the equilibrium outcomes and how they change with the consumer profiling accuracy σ.

Proposition 7. *Under the consumer-surplus-based recommendation system, a symmetric pure-strategy equilibrium exists if and only if* $\sigma > \underline{\sigma}$ *(the threshold* $\underline{\sigma}$ *is defined in the appendix). Under this condition:*

(1) the equilibrium price is $p^{CB*} = \frac{\alpha}{2k(1-z^2)}[k(1-z^2) + 4\tilde{\sigma}(2 - z - k(1 - z + z^2)) - ((k(1-z^2) + 4\tilde{\sigma}(2 - z - k(1 - z + z^2)))^2 - 4\tilde{\sigma}k(1-z)(1-z^2)(2(2-k(1-z)) + k(1+z)\tilde{\sigma}))^{\frac{1}{2}}]$ *for both sellers, and it increases with* σ*;*

(2) Consumer surplus (and the consumer-oriented marketplace's payoff) will decrease with σ *if* $\frac{\partial p^{CB*}}{\partial \sigma}$ *is sufficiently large. The sellers' profit increases with* σ*.*

Proposition 7 presents the equilibrium outcomes and how they change with the profiling accuracy σ. Under a consumer-surplus-based recommendation system, as σ increases, the recommendation-competition incentive becomes weaker and the valuation-exploitation incentive stronger, both raising the equilibrium price. Hence, a higher σ will increase the sellers' profit because of the alleviation of the sellers' competition and the more accurate recommendations. By contrast, if the equilibrium price increases with σ sufficiently fast, despite the better recommendation accuracy, consumer surplus will decrease and thus the consumer-oriented marketplace will become worse off. Put differently, a higher profiling accuracy can *backfire* on the consumer-oriented marketplace after considering the sellers' strategic pricing decisions. The finding is analogous to the case of the profit-oriented marketplace, whose profit can decrease with σ when accounting for the sellers' strategic pricing decision (Proposition 5).

Result 2 illustrates how the equilibrium outcomes differ depending on whether the marketplace is consumer- or profit-oriented.

Result 2. *Compared to when a profit-oriented marketplace uses a profit-based recommendation system, when a consumer-oriented marketplace uses a consumer-surplus-based system, the equilibrium price is lower, the sellers' and the marketplace's profits are lower, and consumer surplus is higher.*

Because recommendation competition propels the sellers to set lower prices with a consumer-oriented marketplace than with a profit-oriented one, the equilibrium price is lower, the sellers' profits are lower, and consumers surplus is higher in the former case than in the latter. Hence, the marketplace's profit-orientation benefits the sellers, but its consumer-orientation benefits the consumers.[13]

5.2. Dual-orientation Marketplace

In this subsection, we study a general setting where the marketplace has dual orientations of improving its profit and consumer surplus simultaneously. Specifically, we consider a dual-orientation marketplace with a payoff function $W = (1 - s) \cdot \Pi + s \cdot CS$, where $s \in [0,1]$ captures how much the marketplace weighs consumer surplus relative to its profit. Accordingly, we analyze a dual-goal recommendation system that recommends a product j with the highest $w_{ij} = (1 - s) \cdot E[\Pi_{ij}] + s \cdot E[CS_{ij}]$ to consumer i, where Π_{ij} is this consumer's contribution to the marketplace's profit and CS_{ij} is her surplus.

Given the technical complexities, we numerically solve the equilibrium outcome. We find that the key features of the sellers' pricing competition remain the same: The magnitude of their recommendation-competition incentive is proportional to $1/\sigma$, the magnitude of their valuation-exploitation incentive is proportional to σ, and the price-undercutting incentive is independent of σ. Results under the case of the profit-oriented marketplace (the consumer-oriented marketplace) stay qualitatively the same when the

[13] The marketplace's payoffs are defined differently and hence incomparable between the two cases.

parameter s is sufficiently low (high). In addition, similar to our previous findings, a higher profiling accuracy can backfire on the marketplace. When the marketplace cares more about consumer surplus (s is larger), the equilibrium price will be lower, the consumers are better off, and the sellers receive less profit. More detailed discussion is presented in the Online Appendix.

6. Extensions

In this section, we extend our results by altering or relaxing a few assumptions in the main model. Section 6.1 shows that our results are robust when consumers have unit demand for the products. Section 6.2 finds that the marketplace can improve its profit (and even achieve its first-best profit) by emphasizing the product's profit margin over its sales quantity in its recommendation decisions. Finally, Section 6.3 demonstrates the robustness of our results when the marketplace endogenizes its commission rate.

6.1. Unit-demand Model

This subsection shows our results are robust when consumers have unit demand for the products. Consumers have horizontally differentiated preferences for the two products and demand at most one unit of either product. Specifically, a consumer belongs to one of the two possible preference types $l \in \{a, b\}$, indicating which product the consumer prefers more in expectation. If consumer i's preference type is $l = a$, her utility is $u_{aA,i} = V_H - hp_A + \epsilon_{iA}$ if she buys product A, $u_{aB,i} = V_L - hp_B + \epsilon_{iB}$ if she buys product B, and $u_{0i} = \epsilon_{i0}$ if she chooses the outside option. $V_H > V_L$ indicates that this consumer prefers product A to product B, $h > 0$ captures the consumers' price sensitivity, and ϵ_{ij}'s and ϵ_{i0}'s are i.i.d. and follow the standard Gumbel distribution. By contrast, if consumer i's preference type is $l = b$, her utility is $u_{bA,i} = V_L - hp_A + \epsilon_{iA}$ if she buys product A, $u_{aB,i} = V_H - hp_B + \epsilon_{iB}$ if she buys product B, and $u_{0i} = \epsilon_{i0}$ if she chooses the outside option. The size for each type of consumers is $\Pr(l = a) = \Pr(l = b) = \frac{1}{2}$.

The marketplace draws a signal $\hat{t}_i \in [-\frac{1}{2}, \frac{1}{2}]$ for each consumer, which indicates this consumer's preference type. A higher (lower) $\hat{t}_i$ indicates a higher likelihood that the consumer prefers product A (B) more over the other product. Specifically, conditional on the consumer's true preference type l, the density functions of $\hat{t}_i$ are $f(\hat{t}_i = t | l = a) = 1 + 2\sigma t$ and $f(\hat{t}_i = t | l = b) = 1 - 2\sigma t$. Hence, the unconditional distribution of $\hat{t}$ is uniform on $[-\frac{1}{2}, \frac{1}{2}]$, and the marketplace's posterior belief for a consumer's preference type conditional on her signal is $\Pr(l=a|\hat{t})=\frac{1+2\sigma\hat{t}}{2}$ and $\Pr(l=b|\hat{t})=\frac{1-2\sigma\hat{t}}{2}$. Similar to the main model, $\sigma\in(0,1]$ captures the consumer profiling accuracy—if $\hat{t}$ is positive (negative), the posterior probability of $l=a$ ($l=b$) increases in σ. All other assumptions remain the same as those in the main model.

If the marketplace recommends product A to an uninformed consumer with signal $\hat{t}$, the expected probability that this consumer will buy product A instead of choosing the outside option is $q_U(A|\hat{t})=\frac{1+2\sigma\hat{t}}{2}\frac{e^{V_H-hp_A}}{1+e^{V_H-hp_A}}+\frac{1-2\sigma\hat{t}}{2}\frac{e^{V_L-hp_A}}{1+e^{V_L-hp_A}}$. Similarly, if product B is recommended, the purchase probability for product B is $q_U(B|\hat{t})=\frac{1+2\sigma\hat{t}}{2}\frac{e^{V_L-hp_B}}{1+e^{V_L-hp_B}}+\frac{1-2\sigma\hat{t}}{2}\frac{e^{V_H-hp_B}}{1+e^{V_H-hp_B}}$. By contrast, for an informed consumer, if her preference type is $l=a$, her probability of buying product A is $q_I(A|l=a)=\frac{e^{V_H-hp_A}}{e^{V_H-hp_A}+e^{V_L-hp_B}+1}$, and her probability of buying B is $q_I(B|l=a)=\frac{e^{V_L-hp_B}}{e^{V_H-hp_A}+e^{V_L-hp_B}+1}$. If her preference type is $l=b$, her probability of buying product A is $q_I(A|l=b)=\frac{e^{V_L-hp_A}}{e^{V_L-hp_A}+e^{V_H-hp_B}+1}$, and the probability of buying product B is $q_I(B|l=b)=\frac{e^{V_H-hp_B}}{e^{V_L-hp_A}+e^{V_H-hp_B}+1}$.

Under the profit-based recommendation system, if the marketplace recommends product A to an uninformed consumer with signal $\hat{t}$, the marketplace's expected profit from this recommendation is $\Pi_U(A|\hat{t})=rp_Aq_U(A|\hat{t})=rp_A[\frac{1+2\sigma\hat{t}}{2}\cdot\frac{e^{V_H-hp_A}}{1+e^{V_H-hp_A}}+\frac{1-2\sigma\hat{t}}{2}\cdot\frac{e^{V_L-hp_A}}{1+e^{V_L-hp_A}}]$. Similarly, if the firm recommends product B to this consumer, the marketplace's expected profit is $\Pi_U(B|\hat{t})=rp_Bq_U(B|\hat{t})=rp_B[\frac{1+2\sigma\hat{t}}{2}\frac{e^{V_L-hp_B}}{1+e^{V_L-hp_B}}+\frac{1-2\sigma\hat{t}}{2}\frac{e^{V_H-hp_B}}{1+e^{V_H-hp_B}}]$. The profit-based system will recommend product A to this consumer if and only if $\Pi_U(A|\hat{t})\geq\Pi_U(B|\hat{t})$, which is equivalent to

$$\hat{t}\geq\hat{t}_0=\frac{1}{\sigma}\cdot\frac{p_B\left(\frac{\mathrm{e}^{V_H}}{\mathrm{e}^{hp_B}+\mathrm{e}^{V_H}}+\frac{\mathrm{e}^{V_L}}{\mathrm{e}^{hp_B}+\mathrm{e}^{V_L}}\right)-p_A\left(\frac{\mathrm{e}^{V_H}}{\mathrm{e}^{hp_A}+\mathrm{e}^{V_H}}+\frac{\mathrm{e}^{V_L}}{\mathrm{e}^{hp_A}+\mathrm{e}^{V_L}}\right)}{2\left(p_A\left(\frac{\mathrm{e}^{V_H}}{\mathrm{e}^{hp_A}+\mathrm{e}^{V_H}}-\frac{\mathrm{e}^{V_L}}{\mathrm{e}^{hp_A}+\mathrm{e}^{V_L}}\right)+p_B\left(\frac{\mathrm{e}^{V_H}}{\mathrm{e}^{hp_B}+\mathrm{e}^{V_H}}-\frac{\mathrm{e}^{V_L}}{\mathrm{e}^{hp_B}+\mathrm{e}^{V_L}}\right)\right)}. \tag{10}$$

Similar to the main model, the threshold $\hat{t}_0$ first decreases and then increases in p_A, so the seller's recommendation-competition incentive also encourages the seller to set a medium price. Moreover, the magnitude of the recommendation-competition incentive $|\frac{\partial\hat{t}_0}{\partial p_j}|$ is still proportional to $1/\sigma$. Hence, the main properties of the sellers' recommendation competition will be robust no matter whether consumers have unit demand or continuous demand. In addition, in the Online Appendix, we verify that all the results in the main model stay qualitatively the same under this unit-demand model.

6.2. Emphasizing Profit Margin in Recommendations to Improve Profit

This section shows that the profit-oriented marketplace can improve its profit by assigning more weight on products' profit margins than on their expected sales in the recommendation rule. For illustration, let us consider the recommendation rules with a Cobb-Douglas objective function: the marketplace recommends the uninformed consumer i with the product j that results in the highest $g_{ij}(\hat{t}_i) = (rp_j)^w \cdot (E[q_{ij,U}|\hat{t}_i])^{1-w}$. The parameter $w \in (0,1)$ captures the relative weight this recommendation rule puts on a product's per-unit profit margin (rp_j) compared to its expected demand from this consumer ($E[q_{ij,U}|\hat{t}_i]$). Note that the profit-based recommendation system is a special case with $w = \frac{1}{2}$, which weighs equally on a product's profit margin and its expected demand. The next proposition discusses the properties of the equilibrium price $p^*(w)$, whose exact expression is given in the Online Appendix.

Proposition 8. *The equilibrium price $p^*(w)$ strictly increases with w. Moreover, there exists a unique $w^{**} > \frac{1}{2}$ that induces the sellers to charge the marketplace's first-best price in equilibrium, i.e., $p^*(w^{**}) = p^{**}$, which leads to the first-best profits for the marketplace and for the sellers.*

As w increases, this recommendation system favors more expensive products, incentivizing the sellers to raise their prices to compete for recommendations. Since the equilibrium price under the profit-based system p^{PB*} is lower than the marketplace's first-best price p^{**}, the marketplace should weigh a product's profit margin more heavily than its expected demand ($w > \frac{1}{2}$) to induce the sellers to charge the first-best price. We acknowledge that although this "first-best" recommendation system generates a higher profit for the marketplace than the profit-based system does, in practice this first-best system requires the marketplace to be able to credibly commit to this recommendation rule (e.g., through repeated interactions or reputation). Without the commitment, if a seller sets p^{**}, the other seller will want to set a different price knowing that the marketplace will then deviate to the profit-based recommendation rule, which will maximize its profits after the prices have been set. Additionally, the first-best recommendation system could be more computationally demanding for marketplaces since it requires computing the optimal w^{**}, which is product-category-specific and needs joint structural estimations of the category's demand and supply system as well as predictions of sellers' pricing decisions to different w. By contrast, the profit-based and the price-neutral systems are computationally simpler since they only require estimating a consumers' preference or expected demand for the products, which many established analytics methods can derive.

6.3. Endogenous Commission Rate

Although major marketplaces rarely change their commission rates for most product categories, the marketplaces may adjust the commission rate in the longer run if the consumer profiling accuracy has dramatically changed. This subsection shows that our results are robust if the marketplace can endogenously set the commission rate r. We assume that a seller's profit will be π_0 if it does not sell on the marketplace. Note that our analysis has shown that in our setting where sellers have zero marginal costs, the commission rate will not affect the equilibrium price, the channel profit, or consumer surplus. Given its dominant position, the marketplace will optimally set the commission rate r such that a seller's equilibrium profit is π_0, so the marketplace will receive the rest of the channel profit. All the results in our main analysis will continue to hold qualitatively, and the marketplace's decision on the commission rate will only affect how the channel profit is distributed between the marketplace and the sellers. In a more general setting where sellers' marginal costs are positive, the marketplace can raise the equilibrium price by increasing the commission rate. However, given that too high of a commission rate will lead to sellers' exit, the marketplace cannot keep raising commission to increase the price to its most desired level when π_0 is large. Therefore, recommendation systems will still play an important role in helping the marketplace influence the prices and achieve a greater profit.

7. Conclusion

The advances in AI-based marketing analytics technologies have enabled online marketplaces to understand the needs of each customer and to personalize product recommendations better than ever. In practice, many online marketplaces tend to recommend each customer with products yielding higher expected profit, giving third-party sellers incentives to adjust prices to compete for recommendations. Our paper studies how the sellers compete for recommendations and how this competition subsequently affects all the participants in the online eco-system. We offer managerial insights on the following questions.

First, how should a seller set its price under the profit-based recommendation system? Our research identifies three incentives that a seller needs to consider in its pricing decision under the profit-based recommendation system. First, because the product price can influence the likelihood of the marketplace's recommendation, the seller has an incentive to set its price such that its product can be recommended to more consumers. This recommendation-competition incentive encourages a seller to set a medium price that tends to maximize the marketplace's profit from the (uninformed) consumers with relatively neutral preferences between the competing products. Second, because its product is more likely to be recommended to consumers with higher valuations for this product, a seller has an incentive to set a relatively high price to exploit these consumers' stronger preferences. Third, a seller also has an incentive to undercut its rival with a relatively low price to compete for the informed consumers, who know and consider both products in the market. In order to optimize its pricing decision, each seller needs to account for all three incentives above. In addition, cutting its price by too much can hurt a seller's demand because the marketplace will be less likely to recommend its product.

Second, under the profit-based recommendation system, how does the marketplace's consumer profiling accuracy affect all the participants in the online eco-system? We find that when the marketplace can more precisely identify consumer preferences, sellers' recommendation-competition incentive becomes weaker, but their value-exploitation incentive becomes stronger, resulting in a U-shaped pattern in the equilibrium price. When a higher consumer profiling accuracy sharply reduces the equilibrium price, despite more accurate recommendations, the profits for the marketplace and the sellers can decrease, while consumers are better off. Note that this result holds even without considering the direct cost of personalization that is likely to increase in the profiling accuracy. Hence, a marketplace can be more profitable to adopt a less personalized recommendation system, in the extreme case, an impersonalized one. Relatedly, regulations that restrict the marketplace's ability of acquiring or using consumer data, such as GDPR and CCPA, can help alleviate seller competition and benefit the marketplace.

Third, when should the marketplace incorporate the products' pricing information in its recommendation system? Broadly, this question relates to how the marketplace should design its recommendation system. An attempting answer is to always use the pricing information and recommend products that lead to the highest expected profits for the marketplace. After all, more information is generally considered to be helpful. However, our analysis shows that doing so can reduce the marketplace's profit if the sellers' strategic pricing responses to the recommendation system are accounted for. We demonstrate that excluding the pricing information can prevent sellers' recommendation competition and increase the marketplace's profit margin and its overall profit when its consumer profiling accuracy is already sufficiently high. These results may help explain why in practice some marketplaces, e.g., Steam, have decided to exclude pricing information in their recommendation systems when they are able to predict consumer preferences better.

Finally, what happens when a marketplace has a consumer orientation? When the marketplace aims to maximize consumer surplus instead of profits, we find that sellers always benefit from an increase in the consumer profiling accuracy. Despite the better matching between recommended products and consumers enabled by the improved profiling accuracy, consumer surplus can decrease, and the consumer-oriented marketplace will become worse off. This finding echoes our result from the case of the profit-oriented marketplace, whose payoff can also decrease with a higher profiling accuracy.

Although our analysis focuses on the scenario in which the marketplace recommends consumers with product categories that they either may have not been aware of or not actively considering, our results also apply to other scenarios in which consumers actively search a product category or search for a specific product. If some consumers search a product category, the marketplace can recommend a product by making it salient in the consumers' search results. As discussed earlier, those who consider only the recommended product will be the uninformed consumers, and those who also search for the other unrecommended product will be the informed consumers. Similarly, if some consumers search for a specific product, one can show that in a symmetric equilibrium the marketplace will optimally recommend the other competing product, effectively making these consumers informed consumers.

We conclude this paper by discussing several directions for future research. First, our model has considered the case with two sellers to illustrate the main tradeoffs concisely and clearly. Future research could expand the analysis to the situation with multiple sellers. We expect most of our results to stay qualitatively unchanged. In addition, we conjecture that as the number of sellers increases, a seller's recommendation-competition incentive will strengthen because it becomes more important for the seller to stand out from other sellers to enter consumers' "exclusive" consideration set. Hence, the magnitude of our results may increase. Second, one can examine the long-term impact of the profit-based recommendation system on the market outcomes, such as how the system can influence seller entry or exit in the marketplace. Our results suggest that the profit-based recommendation system, compared with the price-neutral one, tends to increase the sellers' profits when the consumer profiling accuracy is relatively low. In this case, seller entry is more likely to happen, which can further benefit the marketplace. By contrast, when the consumer profiling accuracy is high, more seller exit may happen under the profit-based recommendation system. Relatedly, our paper considers a single-period setting. Marketplaces may further improve its long-term profit by, for example, recommending products that maximizes consumers' lifetime value. Future research can investigate the long-term impact of recommendation systems on different participants. Third, one can extend our model to endogenize the marketplace's consumer profiling accuracy investment by allowing the marketplace to incur a fixed cost on improving σ. Our current analysis focuses on the marketplace's revenue gross of the fixed cost, and the marketplace's net profit will be the difference between the gross revenue and the fixed cost. Our current results imply that the marketplace may not want to improve its profiling accuracy because of the sellers' recommendation competition even if it is costless to do so. Lastly, our model predictions are consistent with some business practices, for example, Steam's change of its recommendation system. Meanwhile, the extant empirical research about the profit-based recommendation system has not accounted for the sellers' strategic pricing decisions. We hope that this paper can motivate more empirical research about personalized recommendation systems to consider sellers' strategic pricing decisions and systematically analyze their impact on consumer welfare.

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