https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Vol. 71, No. 11, November 2025, pp. 9812–9830
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

"Sherlocking" and Platform Information Policy

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Received: March 9, 2024
Revised: December 8, 2024
Accepted: February 24, 2025
Published Online in Articles in Advance: April 7, 2025

https://doi.org/10.1287/mnsc.2024.05215

Abstract. Platform-run marketplaces may exploit third-party sellers' data to develop competing products, but the threat of future competition can deter sellers' entry. We explore how this trade-off affects the platform's entry on the marketplace and the referral fee it charges to the third-party sellers. We first characterize the platform's optimal fee under different degrees of commitment on its own entry policy. We show that full commitment maximizes not only the platform's payoff but also consumer surplus, as the associated fee induces maximal entry by the sellers. Next, we show how and when the platform's policy on information sharing between its marketplace and product divisions can substitute for its commitment to entry. We characterize the platform's optimal information policy and examine how it interacts with the platform's fee structure. We show that an outright ban on information sharing between the platform's divisions can reduce consumer welfare as it may lead to a higher referral fee that thwarts sellers' entry. Our findings highlight the importance of considering the platform's fee structure as a strategic response in the policy debates on marketplace regulation.

History: Accepted by Alfonso Gambardella, business strategy.

Funding: J. P. Choi is supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea [Grant NRF-2023S1A5A2A01074511]. K. Kim is supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea [Grant NRF-2020S1A5A2A03043516].

Keywords: platform marketplace • referral fee • entry • information design

1. Introduction

Platform-run marketplaces facilitate product discovery by enabling consumers to find obscure niche offerings that match their preferences.[1] However, it is common practice for such platforms to adopt a hybrid business model where they not only earn revenue from the third-party sellers by charging them a referral fee (i.e., a commission payment for every sales transaction on the platform) but also directly compete with the sellers by introducing their own private-label products. Often accused of being "both player and referee," the hybrid marketplace platform can be an uneven playing field as the platform can potentially use the third-party sellers' market data to design its own products and promote its private-label options over its competitors' offerings.[2]

For example, consider Apple's App Store, the only channel through which developers can distribute their apps to the end users on iPhone and iPad platforms. However, Apple is also a provider of apps that potentially compete against the third-party products, and has been accused of engaging in anticompetitive conduct often referred to as "Sherlocking": it allegedly uses market data to target and copy profitable third-party apps, rendering them obsolete and driving the third-party developers out of business.[3] Similar concerns were also raised for the leading e-commerce platform, Amazon Marketplace, as it is alleged to have improperly shared third-party sellers' data with its division in charge of private-label product developments (Mattioli 2020).

This type of predatory behavior by dominant platforms and its associated concerns have led to a variety of regulatory policy proposals. In the United States, policy makers have proposed structural separation that would prohibit hybrid business models by dominant platforms (Warren 2019). In contrast, the European Union (E.U.) Digital Markets Act calls for behavioral restrictions on the use of proprietary data generated through activities by the sellers and end users on the gatekeeper platforms.

However, Sherlocking is not the only strategic lever available to the platform for extracting the profits from the third-party sellers; it can do the same through the referral fees. Indeed, if a platform could commit to intertemporal price discrimination (in referral fees), it could extract a significant part of the third-party sellers' surplus without relying on entry via imitation and self-preferencing. Sherlocking becomes a key channel of surplus extraction as such price discrimination is typically infeasible and the platforms are constrained to maintain a uniform fees structure over time.[4]

But even when "Sherlocking" is ex-post optimal, the platform's choice of referral fee remains a critical component of its competitive strategy. The threat of Sherlocking deters sellers' entry, which is not only detrimental to the social welfare but also reduces the platform's payoff. In response, the platform may strategically set its referral fees to limit its own entry, and balance the trade-off between the ex-post gains from imitating the sellers' product and the ex-ante loss from reduced entry by the third-party sellers. In particular, when the platform cannot directly commit to its entry policy, a high referral fee may serve as a commitment device: it can mute the platform's entry incentives by raising its opportunity cost of entry.

The goal of this paper is to (i) analyze the interplay between the platform's fee structure and its entry decisions in the face of the aforementioned trade-off, and (ii) explore the platform's strategic response to regulations on entry, either in the form of direct prohibition or through restrictions on its usage of the third-party data that informs its entry policy. We first analyze the optimal fee structure of the platform when it can commit to its entry policy. Next, we consider the case where it cannot, and explore when and how the platform can use its data sharing/usage policy to replicate the outcome under entry commitment. Finally, we draw out the welfare implications of our findings for some of the key policy proposals on the platform's entry regulation.

We develop a tractable model of a platform-run marketplace where the platform charges a referral fee to the sellers for access to the marketplace and may also subsequently launch its own private-label product by copying the seller. The game unfolds as follows: first, a third-party seller privately observes the profitability of his product, that is, his "type", and, given the referral fee, decides whether to enter the marketplace by incurring a fixed cost. After the seller's entry, the platform may subsequently observe the type and decide whether to enter the market by imitating the seller's product.

Our first set of results explore how the optimal referral fee varies with the platform's commitment power over its entry decision. If the platform operates only as a marketplace (instead of operating in hybrid mode) its optimal fee trades off extracting more from the entering sellers against encouraging sellers' entry. How does the fee structure change if the platform adopts a hybrid mode? The answer depends crucially on whether the platform can commit to its entry policy.

In the absence of any entry commitment, the platform would enter whenever it is profitable to do so. Anticipating that, a seller, particularly the more profitable types, may stay out of the marketplace as he expects the platform to subsequently imitate his product and put him out of business. But committing to a high referral fee reduces such threat of imitation as the platform now has more to lose in terms of foregone fees should it decide to "Sherlock" a third-party seller. By raising the referral fee, the platform loses the relatively less profitable types of the seller, but the resulting loss is more than compensated as the high fee would encourage the more lucrative seller types to enter (ones who were staying out due to imitation threat). That is, a high fee allays the sellers' concern about future competition and serves as a commitment device for the platform. We show that the platform may raise its fee to a sufficiently high level—one that is at least as large as the optimal fee the platform would have set if it were operating as a marketplace only—so that product imitation is never optimal regardless of the seller's type.

However, if the platform can use, and commit to, a nuanced (type-contingent) entry policy, then it would set a fee that is even lower than the one it would have set if it were to operate only as a marketplace. When the platform can commit to its entry decision, it can induce even a high-type seller—ones that are more vulnerable to imitation—to enter by limiting its own likelihood of entry, and extract (a part of) the rent the seller earns on the marketplace. In particular, the platform extracts all rents from the high-type sellers who are worth imitating, and have a stronger incentive to induce more seller types to enter. Consequently, it further lowers its referral fees.

While the platform is better off when it can commit to its entry decision, in many scenarios it may lack such commitment power, especially when the platform can capture a third-party seller's market share by introducing a close substitute that may not be a direct imitation of the seller's product.[5] However, it might be possible for the platform to commit to its data usage policy. Such a policy stipulates the extent to which the platform's marketplace division shares the third-party sellers' data with its own product division.

In practice, a platform may either completely block its product division's access to its marketplace division's data, or could implement a more subtle policy where the data are shared at a prespecified level of aggregation across the sellers and the product types. Aggregation obfuscates information on any specific seller's product, and may reduce the likelihood that a seller would be targeted for "Sherlocking".[6] Furthermore, the nature of such shared data may be discoverable and verifiable by the court of law. Indeed, various regulatory proposals on data usage, for example, the E.U. Digital Markets Act, that seek to regulate the level of aggregation and anonymity in third-party data shared between the platform divisions rely on the verifiability of the shared data. One may also interpret the platform's data usage policy as a "privacy policy" offered to third-party sellers. Privacy policies specify what data are collected by the platform for its own commercial purposes, and are routinely used in e-commerce.[7]

If the platform cannot commit to entry, can it use its data sharing policy to implement the entry-commitment outcome? To explore this question, we model the platform's data sharing policy as an information design problem. Instead of directly observing the seller's type, the platform commits to observe only a signal on the seller's type that is generated from a prespecified signal structure. We assume that the platform chooses its referral fee and the signal structure at the beginning of the game.

A sophisticated information policy may enable the platform to replicate its entry- commitment outcome by producing an entry-favorable signal (equivalently, entry recommendation) if and only when the seller's type is such that in the entry-commitment case, the platform would have opted to enter. However, the information policy must satisfy the platform's own incentives regarding whether to enter or not up on receiving such a signal; that is, the platform's "obedience" constraints need to hold.

We derive a general condition under which the platform can secure its entry-commitment payoff through its information sharing policy. The condition holds if the cost of entry is relatively large and it takes relatively longer for the platform to imitate the seller's product. If this condition fails, then for any referral fee the platform sets, the associated optimal signal calls for excluding some of the intermediate types of the seller. The optimal referral fee now balances a trade-off between the gains from enhanced entry by the seller (particularly of the intermediate types) and the loss due to distortions from the optimal fee under entry commitment.

Our findings have sharp implications for key policy recommendations on regulation of hybrid marketplaces, such as a ban on hybrid mode and a ban on the use of third-party sellers' information for the launch of private-level products. Margrethe Vestager, European Commissioner for Competition, highlights the limitations of ex post antitrust investigations, likening them to a never-ending game of "whack-a-mole." She advocates for "ex ante" regulation to proactively address systemic anticompetitive behavior.[8] However, due to the regulatory response of the platform in its choice of referral fee, the welfare implications of such policies are often ambiguous, and under some settings, they could be welfare reducing.

For example, as discussed earlier, under no regulation on the mode of operation and information usage the platform may be able to implement the entry-commitment outcome through its information policy. In that case, the associated referral fee is lower than its counterpart when the platform operates only as a marketplace. Thus, banning hybrid mode may result in a much higher referral fee that stifles sellers' entry and reduces the welfare for both the sellers and the consumers.

A policy that only prohibits information usage (i.e., allows hybrid mode as long as the platform does not use the third-party sellers' data for its own entry decision) may also have a negative welfare implication. In this case, the platform would infer the sellers' profitability from their entry decision, which, in turn, depends on the platform's entry decision. We show that in equilibrium the platform sets a sufficiently high referral fee so as to remove its own incentive to enter the marketplace. As a result, the welfare implication of the ban remains ambiguous, as the optimal referral fee under the marketplace mode and the hybrid mode cannot be ranked in general.

Regulations banning hybrid platforms have been discussed by various agencies, although they have not been implemented as yet. Firms' response to current regulations targeting related anticompetitive behavior suggests that the unintended welfare implications of regulation, as discussed above, are not a mere theoretical possibility. For example, in 2018, the E.U. fined Google €4.34 billion for abusing its dominance in the mobile phone market by engaging in illegal tying practices that forced consumers and device manufacturers to use its own services, such as Google Search, Chrome, and the Play Store.[9] This type of bundling is considered exclusionary conduct, like the practice of "Sherlocking," as it promotes Google's own services at the expense of rival products. In response to the ruling, Google announced it would comply by unbundling the Google Android app package but considered charging device manufacturers as much as $40 per device for the Android licensing, which was previously freely available.[10] Google's behavior indicates that in response to regulations on purported exclusionary behavior, the firm may indeed adapt its pricing strategy to the detriment of its customers, and the welfare consequences of any such regulation can only be assessed by taking the resulting price effects into consideration.

1.1. Related Literature

Our paper is related to several recent papers that address various issues associated with platform marketplaces. Madsen and Vellodi (2025) analyze the implications of platforms' use of proprietary marketplace sales data to target the introduction of private-level products. They explore how innovation incentives in digital markets can be shaped by various policies/regulations on the platforms' data usage. Even though there are some parallels between their paper and ours in terms of motivations and questions addressed, our paper differs from theirs in three major respects. First, they focus on the case where the ad-valorem referral fee is fixed and do not characterize the optimal referral fee. In contrast, the interplay among the optimal referral fee, entry decisions, and data usage is one of the main foci of our paper. Second, they consider the seller's ex ante entry incentive (without knowing his type), while we focus on the seller's interim incentive. This drives several significant differences in the results and analysis. For example, in their paper, the seller's (entrepreneur's) entry is always characterized by a cutoff type (cost), which is no longer the case in our model (see Section 5). Finally, they consider a regulator's problem regarding when to allow the platform to observe (what) marketplace data, while we focus on the platform's own data policy. In other words, they study a regulator's information design problem, while ours is the platform's information design problem.

In another recent paper, Hagiu et al. (2022) build a model of a platform that can choose to offer a marketplace to innovative third-party sellers and convenience benefits to consumers for transactions. They consider three types of platform business models: marketplace mode, seller mode, and dual mode where a platform sells on its own marketplace.[11] Given antitrust concerns about dominant platforms' adoption of the dual mode along with product imitation and self-preferencing, they analyze the effects of various policy options including an outright ban on the dual mode. They show that the policy outcomes crucially depend on the platform's policy-induced endogenous choice of business models. However, the setup and focus of their model are very different from ours. For instance, the dual mode platform in their model can still sell its own existing product in the absence of entry by an innovative seller, and in their "exploitative" equilibrium a referral fee is set high to shield its own product from the innovative seller. In our model, entry by a third party is essential for the platform to sell its own product because we focus on the product discovery aspect of marketplaces.[12] Thus, the role of a referral fee is very different in our model in that it serves as a commitment device not to imitate the third-party seller's product to induce more entry.

Anderson and Bedre-Defolie (2024) develop an analytical framework to investigate interactions between monopolistically competitive third-party sellers and a hybrid platform. As in this paper, the determination of a referral fee is a central question. However, the referral fee in their model is used as a mechanism of "insidious steering" by the hybrid platform to steer demand to its own products. In addition, there is no information elicitation from third-party sellers in their model.

In focusing on the product discovery aspect of marketplaces and addressing the issue of free-riding on the information provided by third-party sellers, our paper is related to Hervas-Drane and Shelegia (2022). They also assume the existence of "unobserved" products whose existence can be identified only through running a marketplace with dispersed information. In such a framework, they investigate incentives for a retailer to switch from a pure seller to a dual mode and the competitive effects from third parties associated with such a switch. One feature of their model is that the entry decision depends only on the referral fee, but is independent of the platform's ex post entry decision because they assume no fixed cost of entry. Thus, the issue of commitment does not arise in their model. In addition, their paper does not address the relevant issues from the information design perspective.

Finally, on the empirical side, Zhu and Liu (2018) investigate Amazon's entry pattern into third-party sellers' product spaces and show that Amazon is more likely to target successful product spaces. Raval (2022) shows that Amazon steers consumers to a first-party offer sold by its retail arm ("Amazon Retail") over third-party offers. In a similar vein, Chen and Tsai (2024) analyze Amazon's "Frequently Bought Together" recommendation system and demonstrate that hybrid platforms have biased incentives for product recommendation. These papers empirically validate our modeling approach on the platform's imitation and self-promotion strategies.

This paper is structured as follows. Section 2 presents our model. We provide two benchmark analyses in Section 3 that highlight how the potential of platform's entry (or lack thereof) affects the seller's entry decision. Section 4 explores the case where the platform has full commitment power over its entry decision. The optimal information policy is analyzed in Section 5. Section 6 discusses the welfare implications of some key policy recommendations in light of our findings. A few extensions of our baseline model are considered in Section 7. The final section, Section 8, presents a conclusion. All proofs are given in Appendix A.

2. Model

We describe the model below by elaborating on its three key components: *players*, *market interactions*, and *payoffs*.

Players: A platform owner P runs a marketplace where a (representative) seller S may bring his product to reach potential customers.

Market interactions: The marketplace operates for two periods, where the time lengths of the first and second periods are $1-\delta$ and δ, respectively.[13] At the beginning of the game, the platform posts an ad valorem referral fee $r \in [0,1]$ on the seller's profit that remains fixed across the two periods. The seller incurs a fixed cost $K > 0$ to enter the marketplace, and once he enters, he earns a profit of $\theta \in [0,1]$ per unit time if he stays as a monopolist in the marketplace. Crucially, θ is privately known to the seller before he enters the marketplace, and therefore, influences his entry decision. We assume that sellers' marginal cost of production is zero and θ is drawn from a uniform distribution over $[0,1]$.[14]

If the seller enters, then in the first period, he earns $(1-r)(1-\delta)\theta$, while the platform owner P obtains $r(1-\delta)\theta$ as referral fees. At the beginning of the second period, P observes θ (by virtue of running the marketplace with access to the seller's proprietary data) and decides whether to launch its own product by imitating the seller's item. Should P decide to imitate, it faces a fixed cost $K_P > 0$ and earns monopoly profit $\delta\theta$ by steering consumers to its own product with self-preferencing.[15] We assume that S does not have access to any alternative marketplace, and the platform cannot develop the product on its own.

Payoffs: If the seller S does not enter, all players earn 0. If S enters, his (ex-post) aggregate payoff is

$$\pi_S(r,\theta) := (1-\delta)(1-r)\theta - K + (1-\mathbf{1}_E)\delta(1-r)\theta,$$

and P's (ex-post) payoff is

$$\pi_P(r,\theta) := (1-\delta)r\theta + (1-\mathbf{1}_E)\delta r\theta + \mathbf{1}_E(\delta\theta - K_P),$$

where the value of the indicator function $\mathbf{1}_E$ is 1 if the platform enters the market in period 2 and 0 otherwise.

Timeline: The timeline of the game is summarized below:

- *Period* 1. The platform (P) posts a referral fee $r(\geq 0)$. The seller observes his "type" θ and the referral fee r, and decides whether to enter. Period-one payoffs are realized.
- *Period* 2. P observes the realization of θ and decides whether to launch its own product. If P enters, it steers all consumers to its own product. Period-two payoffs are realized.

To focus on a more interesting economic environment where the players' strategic considerations as well as the regulatory policy implications are nontrivial, we impose the following parametric restrictions.

Assumption 1. $1-\delta < K$, $K_P < \delta$, *and* $K < K_P/\delta$.

The first inequality implies that the threat of "Sherlocking" is indeed a major entry deterrent for the third-party sellers. Notice that if the platform enters for sure then the entering seller's payoff is equal to $(1-\delta)(1-r)\theta - K \leq (1-\delta) - K$. Thus, under the first inequality, even the highest type seller ($\theta = 1$) does not enter the marketplace if he expects the platform to steal his business for sure.[16] Now, if the platform enters in the second period then its payoff is equal to $\delta\theta - K_P$. Thus, the second inequality ensures that in the absence of any referral fee (i.e., when $r = 0$), the platform finds it profitable to enter if θ is sufficiently large. The final inequality guarantees that, due to the gain from the first period, the seller has a stronger incentive to enter than the platform. Note that it holds as long as K_P is not significantly lower than K.[17]

We use (weak) Perfect Bayesian Equilibrium as the solution concept.

We conclude this section with the following remarks on our modeling specifications. First, one may interpret the seller's type in terms of the demand state of his product. For example, suppose that the demand function for the seller's product is invariant over time and is given by $D(p,\theta) := \theta d(p)$ where p is the unit price and the parameter θ captures the market thickness. The seller, if selling on the marketplace, would charge the monopoly price $p^m := \arg\max_p pd(p)$ that is independent of the market size and the referral fee, and the same holds for the platform if it launches its own product in the second period. One obtains our modeling setup by normalizing the monopoly profit $p^m d(p^m)$ to 1. This foundation also allows us to formally measure consumer surplus: Let $\mathbf{Pr}_S(\theta)$ denote the probability that a seller of type θ enters the marketplace. Since the platform, upon entry, retains monopoly power by simply replacing the seller, the consumers continue to face the monopoly price p^m regardless of whether the platform enters or not. Therefore, *ex-ante* consumer surplus is given by

$$\begin{aligned} CS &:= \int_0^1 \theta\left[\int \max\{d^{-1}(q) - p^m, 0\}dq\right]\mathbf{Pr}_S(\theta)d\theta \\ &= \int \max\{d^{-1}(q) - p^m, 0\}dq \cdot \int \theta \mathbf{Pr}_S(\theta)d\theta. \end{aligned}$$

Note that this value depends only on the sellers' entry decisions. In what follows, whenever applicable, we refer to this measure as consumer surplus.

Second, one may interpret the relative "lengths" of the two periods as the duration of learning and monetizing phases of a product development process. Specifically, $1-\delta$ can be interpreted as the relative length of time it takes for the platform to acquire relevant information on the profitability of the product, and δ reflects the time span over which the platform gets to exploit this information.

Third, we have modeled the referral fee as an ad valorem fee levied on the seller's profit. Neither of these two assumptions is central to our findings. Our analysis remains qualitatively unchanged if one considers a specific fee (per transaction) instead of ad valorem fee. Furthermore, in our setup, an ad valorem fee levied on the seller's profit is quantitatively equivalent to levying it on the price, as we have assumed the seller's marginal cost of production to be zero. However, with positive marginal cost, fee levied on profit is no longer equivalent to fee levied on price: if we continue to assume that the ad valorem fees are levied on the seller's profit, the analysis remains unaffected, but if the fees are levied on price it leads to a double marginalization problem and compromises the algebraic tractability of our model. Nevertheless, as we elaborate in Appendix C, some of our key results continue to hold as long as the marginal cost is not too large.

Finally, our assumption of time-invariant referral fee reflects the practical limitations on fee adjustments over time (as mentioned in Footnote 4), and should not be interpreted as the platform's ability to commit to long-term contracts.[18] In fact, if the platform were to have such commitment power, extracting the sellers' surplus through time-varying and type-contingent referral fees would be more profitable than doing so via Sherlocking, as it saves on the platform's duplicative entry cost K_P. It is the platform's inability to adopt such intertemporal price discrimination policy that makes Sherlocking a relevant channel for surplus extraction.

3. Benchmarks on Platform's Entry

We begin by analyzing two benchmark cases, one in which the platform never imitates the seller's product and the other in which the platform imitates the seller's product whenever it is profitable to do so. Note that the first case can be interpreted as the case in which the platform commits to not imitate the seller's product, while the second case reflects the scenario where the platform has no commitment power over its own entry decision.

3.1. No Entry by the Platform

If the seller does not face any threat of entry from the platform, the platform's action affects the seller's entry only through the referral fee. Given r, the seller (S) enters if and only if

$$(1-r)\theta \geq K \Longleftrightarrow \theta \geq \theta_S(r) := \min\left\{\frac{K}{1-r}, 1\right\}. \quad (1)$$

Therefore, the platform's problem is

$$\mathcal{P}_{NE}: \max_r \ \Pi_P^{NE}(r) := \int_{\theta_S(r)}^1 r\theta d\theta,$$

and its interior solution, denoted by r^{NE}, satisfies

$$\frac{1}{2}(1-\theta_S(r^{NE})^2) = r^{NE}\theta_S(r^{NE})\theta_S'(r^{NE}).$$

This is a standard monopoly pricing problem. Intuitively, an increase of r allows the platform to extract more from the seller conditional on entry (i.e., $\theta \in (\theta_S, 1]$). However, it reduces the seller's entry incentives and the platform loses the referral fee from the marginal seller type θ_S. In the above equation, the left-hand side captures the former marginal benefit, while the right-hand side represents the latter marginal cost. As the optimal fee is strictly positive, there is too little entry compared with the socially efficient level (note that it is efficient for the seller to enter if and only if $\theta \geq K$).

3.2. Entry by the Platform Whenever Profitable

Next, consider the case where the platform can imitate the seller's product and enter the market whenever profitable. Given θ, the platform prefers to enter if and only if

$$\delta\theta - K_P \geq \delta r\theta \Longleftrightarrow \theta \geq \theta_P(r) := \min\left\{\frac{K_P}{\delta(1-r)}, 1\right\}. \quad (2)$$

So, given r, the type-θ seller's payoff from entry is:

$$\pi_S(r;\theta) = \begin{cases} (1-r)\theta & \text{if } \theta \leq \theta_P(r) \\ (1-\delta)(1-r)\theta & \text{otherwise.} \end{cases}$$

Notice that the last inequality of Assumption 1 leads to $\theta_S(r) \leq \theta_P(r)$ where the cutoff $\theta_S(r)$ is as defined in (1). This implies that the seller enters if and only if $\theta \in [\theta_S(r), \theta_P(r))$, so the platform's problem is given by[19]

$$\mathcal{P}_{NC}: \max_r \ \Pi_P^{NC}(r) := \int_{\theta_S(r)}^{\theta_P(r)} r\theta d\theta.$$

Let r^{NC} be the solution to $\mathcal{P}_{NC}$. Then we have the following result.

Proposition 1. *The optimal referral fee set by the platform when it has no commitment power over its own entry decision is at least as large as the optimal fee it would set when it commits to not enter by imitating the seller's product; that is,* $r^{NC} \geq r^{NE}$.

To see the intuition for this result, recall that a lack of commitment by the platform causes the most lucrative seller types ($\theta \geq \theta_P$) not to enter. Raising r helps reduce associated losses, because it lowers the platform's own entry incentive, thereby encouraging third-party sellers' entry; that is, a higher r helps the platform mitigate its own (no-)commitment problem.[20] Specifically, as r rises, θ_P increases faster than θ_S, so the absolute length of the interval $[\theta_S(r), \theta_P(r)]$ expands (provided that $\theta_P(r) < 1$). This expansion is profitable: even if the average entering type is constant, it would increase the platform's profit. But, the expansion even raises the average entering type as it replaces lower types (around $\theta_S(r)$) with higher types (around $\theta_P(r)$). Consequently, the platform would raise r up to the point where $\theta_P(r) = 1$.

An important implication of this result is that the "no-entry" case explored earlier (in Section 3.1) Pareto dominates the "no-commitment" benchmark. The comparison of the seller's payoff is immediate from Proposition 1. When the platform cannot commit to its entry policy, in equilibrium it chooses a higher referral fee and stifles the seller's entry. The platform's payoffs in the two cases also have the same ranking. As no seller type above θ_P enters, in equilibrium the platform does not benefit from having the option to enter the marketplace: the platform never enters, and fewer types of the sellers enter the marketplace relative to the "no-entry" case. Finally, consumes are better off because the seller is more likely to enter (i.e., $\theta_S(r^{NE}) \le \theta_S(r^{NC})$).

4. Full Commitment to Entry

Section 3 highlights the importance of the platform's entry commitment. This section studies the platform's optimal strategy when it could exert full commitment power over its own entry. In particular, we assume that the platform can choose, and commit to, a function $\alpha : [0,1] \times \mathbb{R} \to [0,1]$ where $\alpha(\theta, r)$ represents the probability that it enters conditional on the seller's type being θ.

Given r and $\alpha(\cdot)$, the seller with type θ enters if, and only if,

$$[(1-\delta) + \delta(1-\alpha(\theta, r))](1-r)\theta \ge K. \qquad (E)$$

This implies that the platform's problem can be written as:

$$\max_{r,\alpha(\cdot)} \int_{\Theta_E} [(1-\alpha(\theta,r))r\theta + \alpha(\theta,r)((1-\delta)r\theta + \delta\theta - K_P)]d\theta,$$

where $\Theta_E = \{\theta \in [0,1] \mid (E) \text{ is satisfied}\}$.

As before, given r, the platform has an incentive to enter if and only if $\theta \ge \theta_P(r)$.[21] So, for $\theta < \theta_P(r)$, it is optimal for the platform to set $\alpha(\theta, r) = 0$ (i.e., not to enter); in this case, the seller enters as long as $\theta \in [\theta_S(r), \theta_P(r))$. For $\theta \ge \theta_P(r)$ it is optimal for the platform to raise $\alpha(\theta, r)$ as much as possible subject to the seller's entry constraint (E). This implies that the optimal α is the value that makes (E) bind, that is,

$$\alpha(\theta; r) := \frac{1}{\delta}\left(1 - \frac{K}{(1-r)\theta}\right).$$

It is worth noting that $\theta_P(r)$ and $\theta_S(r)$ are increasing in r, whereas $\alpha(\theta; r)$ is decreasing in r and increasing in θ. Also, it is routine to check that $0 \le \alpha(\theta; r) < 1$ (given Assumption 1). This implies that the platform's optimal commitment problem reduces to:

$$\mathcal{P}_C : \max_{r \in [0,1]} \Pi_P^C(r)$$
$$:= \int_{\theta_S(r)}^{\theta_P(r)} r\theta d\theta + \int_{\theta_P(r)}^{1} \left[\begin{matrix}(1-\delta)r\theta + \\ [\alpha(\theta;r)(\delta\theta - K_P) + (1-\alpha(\theta;r))\delta r\theta]\end{matrix}\right] d\theta.$$

Let r^C be the solution to $\mathcal{P}_C$. Notice that

$$\Pi_P^C(r) - \Pi_P^{NE}(r)$$
$$= \int_{\theta_P(r)}^{1} \alpha(\theta;r)[\delta(1-r)\theta - K_P]d\theta \begin{cases} > 0 & \text{if } r < \bar{r} \\ = 0 & \text{otherwise,} \end{cases}$$

where $\bar{r}$ denotes the value of r such that $\theta_P(r) = 1$, that is, $\bar{r} = 1 - K_P/\delta$. This observation leads to the following result.

Proposition 2. *The optimal referral fee set by the platform when it has full commitment power over its own entry decision is (weakly) lower than the optimal fee it would set when it commits to not enter the marketplace; that is,* $r^C \le r^{NE}$.

In the no-entry benchmark case, the seller obtains positive rents whenever $\theta \ge \theta_S(r)$, whereas in the commitment case, the seller receives no rents whenever $\theta \ge \theta_P(r)$. This implies that the marginal gain of increasing r is higher under the no-entry case (extracting more from seller types in $[\theta_S(r), 1]$) than under the case where the platform can commit to its entry decision (extracting more from the seller types in $[\theta_S(r), \theta_P(r))$ only). The result that $r^C \le r^{NE}$ follows, because the corresponding marginal cost of increasing r—$\theta_S(r)$ type not entering—is identical between the two cases. Notice that under full commitment, the seller's entry incentives are stronger as the referral fee is lower. Also the threat of business stealing does not thwart the seller's entry as, in equilibrium, the platform's likelihood of entry is set at the level where the seller breaks even by deciding to enter.

Compared with the two benchmark cases (in Section 3), with commitment to entry the platform and the consumers are both better off. It is trivial that commitment to entry would benefit the platform as it can always implement the market equilibrium under the "no entry" or "no commitment" case. The consumers are better off as there is more entry due to lowered referral fee (and they pay the same price regardless of platform's subsequent entry decision). However, the seller's payoff vis-a-vis the benchmark cases cannot be ranked as it is affected by two countervailing effects: a lower referral fee induces more entry by the seller (θ_S is lower) but it also makes the platform's entry more likely. Interestingly, this observation opens up the possibility that, relative to the case when the platform cannot enter, some types of the seller may be better off when the platform can commit to its entry decision. In particular, the seller types $\theta \in (\theta_S(r^C), \min\{\theta_S(r^{NE}), \theta_P(r^C)\}]$ now earn a positive rent following entry whereas they would have earned 0 in the scenario where the platform cannot enter the marketplace (and chooses its referral fee r^{NE} accordingly).

5. Optimal Information Policy

We now turn to the situation in which the platform cannot fully commit to its entry decision, but can optimally choose its "information policy", that is, how much information about the profitability of the seller's product it may generate or share with its product division. To evaluate the full potential of the platform's information policy, as in the recent literature on information design, we endow the platform with full flexibility in its choice of information. The following result, however, shows that in our environment, it suffices to restrict attention to binary signals.

Lemma 1. *Without loss of generality, we can limit attention to a signal with binary realizations $x \in \{0,1\}$, where $x=1$ induces the platform to enter and $x=0$ induces the platform to stay out.*

To understand this result, notice that the platform's payoff is linear in θ, so its entry decision depends only on the conditional expectation of θ—in particular, whether it exceeds θ_P or not. All signal realizations leading to the posterior mean below (or above) θ_P can be pooled. Therefore, the outcome by any signal can be replicated by a binary signal, whose realization can be interpreted as an action (entry or not) recommended to the platform.

5.1. Implementing Full Commitment Outcome

We first explore if and when it may be possible for the platform to implement the full commitment outcome characterized in Section 4.

To implement the full commitment outcome, it is necessary and sufficient that the platform enters with probability $\alpha(\theta;r)$ when the seller's type is θ. With a binary signal, this outcome can be induced if and only if the platform uses the following signal structure:

$$\Pr(x=1|\theta) = \begin{cases} \alpha(\theta;r) & \text{if } \theta \ge \theta_P(r) \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

In other words, the platform should observe $x=1$, and so enters, with probability $\alpha(\theta;r)$ whenever $\theta \ge \theta_P(r)$; otherwise, the platform should observe $x=0$ and not enter. By construction, this signal induces the full commitment outcome in Section 4 if and only if the following two obedience constraints hold:

$$\mathbb{E}[\theta|x=0;\, \theta \ge \theta_S(r)] \le \theta_P(r), \tag{OC_0}$$

and

$$\mathbb{E}[\theta|x=1;\, \theta \ge \theta_S(r)] \ge \theta_P(r). \tag{OC_1}$$

That is, conditional on $x=0$, the expectation of θ should be less than $\theta_P(r)$ so that the platform has no incentive to enter. On the contrary, conditional on $x=1$, the expectation of θ should exceed $\theta_P(r)$ so that the platform wishes to enter.

Since $\alpha(\theta;r)>0$ (and so one may observe $x=1$) only when $\theta > \theta_P(r)$, the constraint (OC_1) is always satisfied under the signal structure (3). This implies the following result.

Proposition 3. *The full commitment outcome is implementable by an information policy if and only if the constraint (OC_0) holds for $r=r^C$, which is equivalent to:*

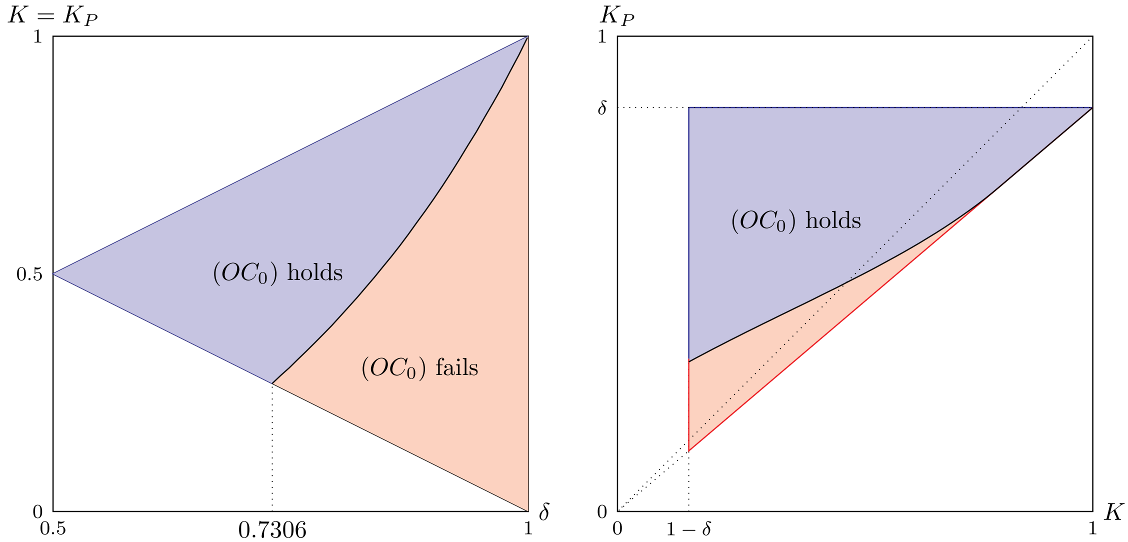
$$\int_{\theta_P(r^C)}^{1} (\theta - \theta_P(r^C))(1-\alpha(\theta;r^C))d\theta \le \int_{\theta_S(r^C)}^{\theta_P(r^C)} (\theta_P(r^C) - \theta)d\theta. \tag{4}$$

To understand Proposition 3, suppose the platform would disobey the action recommendation and enter after observing $x=0$. It would earn positive profit if $\theta > \theta_P(r^C)$ but incur losses if $\theta \in [\theta_S(r^C), \theta_P(r^C))$. The left-hand side of (4) represents the former gains, while the right-hand side captures the latter losses. The platform would not enter (i.e., (OC_0) holds) if and only if the gains from types above $\theta_P(r^C)$ are smaller than the losses from types below $\theta_P(r^C)$. Naturally, (4) holds when $\theta_P(r^C)$ is sufficiently large, $\theta_S(r^C)$ is sufficiently small, and $\alpha(\theta;r^C)$ is overall large.

Figure 1 depicts the parameter region under which (OC_0) holds—so, the commitment outcome can be implemented by an information policy; note that the unshaded region is where Assumption 1 is violated, and hence, not relevant for our analysis. The left panel shows that given K and K_P (we set $K=K_P$), δ should be relatively small. This is because an increase of δ lowers $\theta_P(r^C)$ and $\alpha(\theta;r^C)$, both of which make condition (4) harder to satisfy. Intuitively, δ represents the relative length of the second period; so the larger is δ, the stronger is the platform's incentive to enter. In addition, when δ is high (so the seller's first-period profit is low), the platform should reduce its entry probability (for types above $\theta_P(r^C)$) so as to preserve the seller's entry incentive. But this makes the seller more likely to be of a type above $\theta_P(r^C)$ conditional on $x=0$, further increasing the platform's incentive to enter. This suggests that the platform's information policy is more likely to be effective, when δ—the relative length of the second period—is low. In other words, the longer it takes for the platform to learn about the demand state (i.e., the larger $1-\delta$ is), the more likely it is that the platform may use its information policy as an effective substitute for its commitment to entry.

The right panel of Figure 1 shows that given δ, (OC_0) requires K_P to be not too small relative to K. This is because an increase of K_P raises $\theta_P(r^C)$ (relaxing the inequality in (4)), while an increase of K raises $\theta_S(r^C)$ and lowers $\alpha(\theta;r^C)$ (making the inequality in (4) harder to satisfy). Intuitively, (OC_0) ensures the platform's incentive to *not* enter, which becomes

Figure 1. (Color online) The Parameter Region Where the Full Commitment Outcome Can Be Implemented via Information Design (i.e., (OC_0) Holds Under $r = r^C$)



Note. In the right panel, $\delta = 0.85$.

easier to satisfy as the entry cost K_P rises. To the contrary, an increase of K reduces the seller's incentive to enter, which raises the cutoff $\theta_S(r^C)$ and lowers the platform's entry probabilities $\alpha(\theta; r^C)$. This makes the seller more likely to be a higher type conditional on $x = 0$, increasing the platform's incentive to enter.

5.2. Optimal Signal When Full Commitment Outcome Is Infeasible

What is the optimal information policy for the platform when the full commitment outcome cannot be implemented, that is, what if (4) fails? We explore this case in two steps. First, we study the optimal information policy for a given referral fee, and then examine the profit maximizing fee for the platform.

Fix a value of r. For any seller type θ who enters, let $\gamma(r, \theta)$ denote the probability that the platform receives $x = 1$ (conditional on θ) and, therefore, also enters. For the optimal signal, we must have $\gamma = \alpha$ for all $\theta > \theta_P(r)$; if $\gamma(r, \theta) > \alpha(\theta; r)$, type θ would not enter, and if $\gamma(r, \theta) < \alpha(\theta; r)$, raising γ would relax (OC_0) and yield a higher payoff for the platform. This implies that whenever (OC_0) is violated under the signal structure (3), the optimal signal should dissuade entry for some seller types above θ_P. The following result shows that it is optimal for the platform to deter entry by intermediate seller types.

Proposition 4. *Given a referral fee r such that (OC_0) fails, the optimal binary signal is given as follows: there exist $\theta_* (> \theta_P)$ and $\theta^* \in [\theta_*, 1]$ such that*

$$\Pr(x = 1 | \theta) = \begin{cases} \alpha(\theta; r) & \text{if } \theta \in [\theta_P(r), \theta_*) \cup [\theta^*, 1] \\ 1 & \text{if } \theta \in [\theta_*, \theta^*) \\ 0 & \text{otherwise.} \end{cases} \quad (5)$$

Facing this signal, the seller enters if and only if $\theta \in [\theta_S, \theta_*] \cup [\theta^*, 1]$.

To understand this result, let $\phi : [\theta_P, 1] \to \{0, 1\}$ denote the entry decision of the seller with type above θ_P induced by the platform's information policy. Given this, (OC_0) can be written as

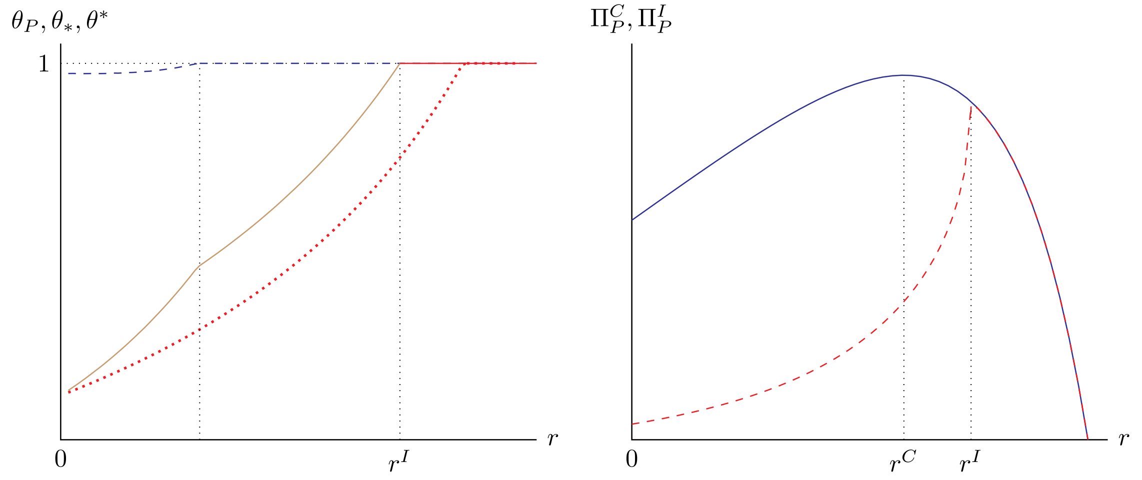
$$\int_{\theta_P}^{1} \phi(\theta)(\theta - \theta_P)(1 - \alpha(\theta; r))d\theta \le \int_{\theta_S}^{\theta_P} (\theta_P - \theta)d\theta.$$

Notice that this inequality necessarily holds if $\phi(\theta) = 0$ for all $\theta \ge \theta_P$ and fails if $\phi(\theta) = 1$ for all $\theta \ge \theta_P$. The platform should find the set of seller types for which $\phi(\theta) = 0$, and the platform's decision depends on how much a seller type would contribute to its profit as well as the implicit cost of including this type via (OC_0). Proposition 4 shows that the platform should exclude intermediate types $[\theta_*, \theta^*)$, that is, induce entry for seller types below θ_* or above θ^*. The seller types that are just above θ_P cost little in terms of (OC_0)—$(\theta - \theta_P)(1 - \alpha(\theta; r))$ is close to 0—but yield nonnegligible profits to the platform. And the seller types that are sufficiently high (i.e., above θ^*), though costly to include, are particularly lucrative to the platform.[22]

Next, consider the optimal referral fee r^I (say) when the platform uses the associated optimal information policy. The platform's optimal referral fee solves (recall that θ_S, θ_P, and α also depend on r):

$$\mathcal{P}_I : \max_{r \in [0,1]} \Pi_P^I(r)$$
$$:= \int_{\theta_S}^{\theta_P} r\theta d\theta + \int_{[\theta_P, \theta_*] \cup [\theta^*, 1]} [(1 - \alpha(\theta))r\theta + \alpha(\theta)((1 - \delta)r\theta + \delta\theta - K_P)]d\theta.$$

Figure 2. (Color online) Optimal Information Policy and Resulting Profits, Conditional on the Referral Fee



Notes. The left panel shows how θ_* (solid), θ^* (dashed), and θ_P (dotted) depend on r, while the right panel compares Platform's commitment profit $\Pi_P^C(r)$ (solid) to its profit $\Pi_P^I(r)$ from the optimal information policy (dashed). In both panels, $K = K_P = 0.4$ and $\delta = 0.85$.

Let r^I be the solution to $\mathcal{P}_I$. Notice that

$$\Pi_P^I(r) = \Pi_P^C(r) - \int_{\theta_*(r)}^{\theta^*(r)} [r\theta + \alpha(\theta; r)[(1-r)\delta\theta - K_P]]d\theta. \tag{6}$$

As noted earlier, if (OC_0) does not bind at r^C, the optimal fee is the same as that under the full commitment case, that is, $r^I = r^C$. In this case, $\theta_*(r^C) = \theta^*(r^C) = 1$ and the platform implements the full commitment outcome. Otherwise, if the platform sets $r = r^C$, in order to meet the (OC_0) constraint it must exclude entry for some of the intermediate types of the seller (i.e., for all types $\theta \in [\theta_*(r), \theta^*(r)]$). Thus, the optimal fee, r^I, may differ from r^C. As (6) indicates, r^I balances the trade-off between the loss relative to the full-commitment payoff and gains from relaxing (OC_0) that may allow for more entry from the intermediate types. That is, as r^I moves away from r^C, the first term in the right-hand side of (6), $\Pi_P^C(r)$, would become smaller but the second term (indicating the loss from excluding the intermediate type) may also decrease.

It is reasonable to conjecture that $r^I > r^C$ (see the right panel of Figure 2). Raising r from r^C would have a second-order effect on Π_P^C (the first term in the expression of Π_P^I in (6)) but it increases θ_P and may relax (OC_0), consequently, having a first-order effect on the gains due to more entry of the intermediate types of the sellers (captured by a decrease in the value of the second term in (6)). Unfortunately, the comparative statics for the cutoffs $\theta_*(r)$ and $\theta^*(r)$ appear to be analytically intractable, and hence, a formal proof of this conjecture remains elusive.[23]

But, numerical solution to the platform's program ($\mathcal{P}_I$) conforms to our conjecture. Increasing r tends to foster more entry as the set of excluded types $[\theta_*(r), \theta^*(r)]$ gets smaller with r (see the left panel of Figure 2). Moreover, the optimal fee r^I is the smallest value of r such that the obedience constraint (OC_0) does not bind. That is, at the optimum, the seller's entry decision continues to follow the cutoff rule where all types $\theta \geq \theta_S$ enter. While there is no exclusion of the intermediate types, the higher fee does restrict the entry of the low types by raising the entry cutoff θ_S.

6. Implications for Regulatory Measures

In light of our discussion above, we can now explore the welfare implications of two salient policy proposals for the regulation of platform-run marketplaces: prohibition on imitating the third-party sellers' products and prohibition on the use of proprietary data about sellers' products. In what follows, we evaluate the effect of each regulation relative to the case studied in Section 5.[24]

The implications for the former policy—ban on imitation—can be readily obtained from our analysis of the case where the platform operates only as a marketplace. The welfare implication of such a policy depends on the relative rankings of r^I and r^{NE}—the equilibrium referral fees when there are no regulations and when the platform commits not to enter. Clearly, when the full commitment case can be implemented through information policy (i.e., we have $r^I = r^C < r^{NE}$), prohibition on the platform's entry is welfare-reducing for the consumers. But otherwise, r^I and r^{NE} cannot be ordered a priori, and when $r^I > r^{NE}$, a ban on imitation improves welfare.[25]

The implications for the latter policy—a ban on the use of (entry) decision-relevant information from the third-party sellers—are more subtle. Our model implies that the welfare implications of such a policy are again ambiguous, and may in fact lead to a welfare loss. Specifically, under the policy, the platform should eliminate its own incentive to imitate the seller, as otherwise the seller would simply not enter regardless of her type, which is the worst outcome for the platform. If this incentive constraint is binding then the platform would set an exceedingly high referral fee as its own commitment device (similar to Section 3.2), which stifles the seller's entry incentive.

To be formal, we first characterize the seller's entry decision. Let $\eta \in [0,1]$ denote the probability that the platform launches its own product by imitating the seller. Given (r,η), a type-θ seller enters if and only if

$$(1-\eta\delta)(1-r)\theta \geq K \Leftrightarrow \theta \geq \theta_S(r,\eta) := \frac{K}{(1-\eta\delta)(1-r)}.$$

As is intuitive, the seller is more likely to enter (i.e., the lower the entry threshold $\theta_S(r,\eta)$ is) when both r and η are smaller.

We now determine the equilibrium value of η by studying the platform's entry incentive. As discussed earlier, for $r \geq \bar{r} := 1 - \frac{K_P}{\delta}$, $\theta_P(r) = 1$, that is, the platform never enters. Therefore, for any such $r \geq \bar{r}$, the seller's entry threshold is

$$\hat{\theta}_S(r) = \min\{\theta_S(r,0), 1\},$$

and the platform's profit is given by

$$\Pi_P^{NI}(r) := \int_{\hat{\theta}_S(r)}^{1} r\theta d\theta = r(1-\hat{\theta}_S(r))\mathbb{E}[\theta \mid \theta \geq \hat{\theta}_S(r)].$$

For $r < \bar{r}$ (equivalently, $\theta_P(r) < 1$), there are multiple equilibria. One can construct a "futile" equilibrium where the seller never enters. In this equilibrium, given $r(<\bar{r})$ the seller believes that the platform will enter with probability 1 (i.e., $\eta = 1$). If so, the seller would not enter regardless of his type. And this outcome can be supported as a perfect Bayesian equilibrium with the platform's belief that assigns probability 1 to $\theta = 1$ as the entering seller's type.

Now we consider the case in which (in equilibrium) the platform does not enter (i.e., $\eta = 0$). This equilibrium exists if and only if the seller's expected type conditional on entering the marketplace exceeds the platform's entry threshold, that is,

$$\mathbb{E}[\theta \mid \theta \geq \hat{\theta}_S(r)] \leq \theta_P(r) \Leftrightarrow \int_{\hat{\theta}_S(r)}^{1} (\theta - \theta_P(r)) d\theta \leq 0. \quad (7)$$

This inequality reduces to

$$\frac{1}{2}(1-\theta_P)^2 - \frac{1}{2}(\hat{\theta}_S - \theta_P)^2 \leq 0 \Leftrightarrow r \geq \underline{r} := 1 - \frac{2K_P}{\delta} + K. \quad (8)$$

It is easy to see that Assumption 1 ensures $\underline{r} < \bar{r}$ and if $r < \underline{r}$, then the above futile equilibrium is the only equilibrium.[26]

The above results imply that with a prohibition on information sharing, the platform never enters but may set a high referral fee. Consequently, the welfare implication of such a policy cannot be ascertained a priori. If the above futile equilibrium is played whenever $r < \bar{r}$ then the platform has no choice but to set $r \geq \bar{r}$. Even if the seller enters whenever $r \in [\underline{r}, \bar{r})$, the optimal referral fee would be $\max\{r^{NE}, \underline{r}\}$ (as the platform does not enter), and as we have already argued, in general, r^{NE} and r^I cannot be ordered. In particular, if $r^I < r^{NE}$, prohibition on information sharing would reduce consumer welfare. It is also worth noting that when $r^{NE} \geq \underline{r}$, a ban on imitation and a ban on third-party data usage—the two seemingly different policies targeting different aspects of the platform's behavior—lead to the same equilibrium outcome, and hence, have exactly the same welfare consequences. The following proposition summarizes the discussion so far.

Proposition 5. *A regulatory ban on the platform's entry in the marketplace or data sharing between its marketplace and product division may be counterproductive and reduce consumer welfare. In particular, the following hold:*

i. *A ban on the platform's entry in the marketplace increases consumer welfare if and only if $r^{NE} < r^I$, that is, the equilibrium referral fee the platform sets when it can commit not to enter is lower than its fee under no regulation on entry or data sharing.*

ii. *A ban on data sharing between the platform's marketplace and product divisions may improve consumer welfare if $r^I \geq r^{NE}$. Otherwise, it necessarily reduces consumer welfare.*

We conclude this section with the following two remarks. First, our model provides a note of caution regarding fee regulations on hybrid platforms. Some recent works on entry incentives in hybrid platforms highlight how platforms may find it optimal to raise referral fees to steer demand toward their own products, stifling entry of third-party sellers (Etro 2023, Anderson and Bedre-Defolie 2024). A natural implication of their findings is that a fee cap could enhance welfare by counteracting this fee increase. However, our analysis in Section 3.2 shows that when the platform cannot commit to its entry or data-sharing policy, such a fee cap could be harmful to consumer surplus. A ceiling on referral fees reduces the platform's opportunity cost of entering the market, and the threat of platform entry reduces the set of seller types willing to enter in the first place, ultimately harming both market competition and consumer welfare.

The key driver of this difference in implications for fee cap is that, in the models of demand steering, the platform can produce its own product and acts as the first mover without relying on the information revealed by third-party sellers. In contrast, in our model, the platform's incentive to imitate third-party sellers' popular products is the primary concern. This "Sherlocking" behavior leads to strategic effects that influence entry decisions and market outcomes, which are absent in the aforementioned models.

Second, apart from the prohibition on imitation and data usage, the regulators may also require a platform to share its proprietary information with the third-party sellers. For instance, Amazon offered to share marketplace data with third-party sellers to settle E.U. antitrust investigations on its alleged preferential treatment of its own retail offers.[27] This policy may have an additional effect of limiting the market power of third-party sellers. However, third-party sellers would be averse to such information being disclosed to potential rival firms beyond the platform itself because it can raise serious issues with firms' privacy and confidential business plans.[28]

7. Discussion

We made several simplifying assumptions in our model to improve its analytical tractability. However, some stylized aspects of our model are not essential for our findings, and the interplay between referral fee and information policy that we highlight in our paper would continue to hold even if we relax some of these assumptions. In this section, we discuss two such extensions of our model: (i) competition between seller and platform following the platform's entry in the second period, and (ii) a case where the platform's entry decision is delegated to the product division manager who may only care about his own division's profits.

7.1. Post-"Sherlocking" Competition

In the main model, we have assumed that once the platform enters, it monopolizes the market with the third-party seller being deprived of opportunities to make any further sales. This is equivalent to an extreme form of self-preferencing by the platform.[29] Indeed, the issue of "Sherlocking" is relevant only if the platform expects to capture a part of the profit to cover its cost of entry. If the product-market competition following the platform's entry is too intense and most of the profits get dissipated to the consumers through lower prices, for example, if Bertrand competition in prices ensues between the seller and the platform resulting in zero profit for both, the platform would de facto commit not to enter in the first place.

Nevertheless, we can easily accommodate the possibility of ex post competition between the platform owner and third parties where both may continue to enjoy some degree of market power. A simple way to capture this case in our setting is to reinterpret the platform's entry probability as the extent to which the platform's own products are featured with prominence (while the third-party products are featured with the complementary probability). Thus, in a market with profitability θ where the platform enters with probability α, self-preferencing by the platform ensures that the seller and the platform earn a profit of $(1-\alpha)\theta$ and $\alpha\theta$, respectively. With this interpretation, the design of the (product recommendation) algorithm plays the same role as information policy in our model in terms of providing entry incentives for third-party sellers.

However, there are two key issues that are worth noting in this context. First, with a self-preferencing algorithm that shares the market with the third-party seller, the platform needs to enter every market for which $\alpha(\theta, r) > 0$. In contrast, with information design, the platform enters only when its signal realization is 1 with probability $\alpha(\theta, r) > 0$. Thus, an information design policy is more efficient than the use of algorithms in terms of saving duplicative entry costs. The regulatory scrutiny on self-preferencing may induce the platform to shy away from the extreme form of self-preferencing and compel it to share the market with third parties when it enters. However, one may argue that such an intervention may entail inefficiency in terms of entry cost duplication.

Second, post-"Sherlocking" competition may indeed lead to lower prices and higher consumer surplus, and in such a setting, regulatory response to "Sherlocking" must balance the trade-off between ex-ante entry incentives of the seller and welfare gains from ex-post competition. Moreover, the platform itself may care about such consumer benefit if it competes with other platforms or when its objective is to grow its consumer base over time. We abstract from this aspect of the post entry competition which can be important in the initial phase of marketplace to get consumers on board.[30] A complete treatment of this issue would call for a formal model of post-"Sherlocking" competition that could considerably impair the analytical tractability of our current framework. Instead, we take the extent of consumer participation in the platform fixed and assume away the price effects of post-"Sherlocking" competition to focus on the effect of "Sherlocking" on the entry incentives for third-party sellers.

7.2. Delegated Entry Decision

In our analysis, we have assumed that the platform's referral fees and entry decisions are both set by its owner. Thus, while deciding on its entry or information policy, the platform weighs its profits from entry against the potential loss of referral fees. In contrast, one may assume that the platform owner delegates the entry decision to its product division manager (the manager could have better information about the platform's production capabilities) but can control the flow of information between the marketplace and the product division. That is, the product division may not readily observe the profitability of various products that are sold on the marketplace, but receives signals on the same as per the platform's information policy. Upon receiving such signals, the division decides whether to enter the marketplace by imitating a seller's product. As the product division does not internalize the opportunity cost of entry in terms of the foregone referral fees, it may enter as long as the expected profit from entry (conditional on the received signal) exceeds its entry cost. This observation has two major implications for our results.

First, when the platform cannot commit to entry and the seller's type (θ) becomes public following the seller's entry (as is the case studied in Section 3.2), the platform would enter if and only if $\delta\theta \geq K_P$, that is, the platform's entry threshold becomes $\theta_P = K_P/\delta$ (that is independent of r), and so the platform's optimal referral fee solves:

$$\Pi_P^{NC}(r) := \max_r \int_{\theta_S(r)}^{\theta_P} r\theta d\theta. \tag{9}$$

Now, Proposition 1 no longer holds, that is, we have $r^{NC} \leq r^{NE}$: the platform's optimal referral fee when it cannot commit to its entry policy would be lower than its optimal fee when it commits not to enter. The argument is simple. When the platform owner decides on both the referral fee and product entry but lacks commitment power over her entry decision, a high referral fee (r) serves as a commitment device. It assures the seller that the platform is less likely to enter as it has a lot to lose in terms of the foregone referral fees. But when the entry decision is delegated at the division level, the product division does not internalize the loss of referral fees and therefore, a higher value of r no longer deters the platform's entry. One may also readily see this from the first-order condition of the platform's problem (9): If r^{NE} is an interior solution, then

$$\begin{aligned}\frac{d}{dr}\Pi_P^{NC}(r^{NE}) &= \int_{\theta_S(r^{NE})}^{\theta_P} \theta d\theta - \theta_S'(r^{NE}) r^{NE} \theta_S(r^{NE}) \\ &< \int_{\theta_S(r^{NE})}^{1} \theta d\theta - \theta_S'(r^{NE}) r^{NE} \theta_S(r^{NE}) = 0.\end{aligned}$$

Second, consider the issue of optimal information policy. One may again ask when the platform could implement its full commitment outcome through a suitably chosen information policy. To address this issue, one may follow the same steps as in Section 5.1, and if entry occurs (by the product division) whenever it believes θ (conditional on the signal it receives) to exceed its entry threshold K_P/δ, then the only change to make is to replace $\theta_P(r^C)$ with $\theta_P = K_P/\delta$. Since $\theta_P < \theta_P(r)$ for any $r > 0$, condition (4) becomes harder to satisfy. This is intuitive because the product division manager's incentives are misaligned with the platform's, so the platform will do necessarily (weakly) worse than in our main model.

8. Conclusion

The use and misuse of proprietary data on third-party sellers by hybrid platforms have drawn considerable attention from the regulatory agencies. Leading platform-run marketplaces, such as Apple App Store and Amazon Marketplace, are alleged to use third-party sellers' product data to target and copy successful products forcing the third-party sellers to exit. Such a practice by the platforms, often termed as "Sherlocking," may stifle innovation and entry by third-parties. The anticompetitive implications of this practice have led several regulatory agencies in the United States and the E.U. to propose limits on the platform's behavior, including ban on imitation and ban on data sharing between the platform's marketplace and product division.

However, the policy on third-party sellers' data usage is not the only strategic lever that a platform can use. The platform also chooses the referral fee for the sellers using their marketplace and decides on its own entry policy accordingly. Thus, in order to assess the platform's response to a regulatory limit on its data policy, one must analyze the interplay between its fee structure, data policy, and entry decision. In this article, we present a stylized model of hybrid platform to explore this issue. Our findings indicate that the platform's commitment to data policy can be a substitute for commitment to entry. In particular, when it takes time to learn about market conditions from the third-party sellers' data and the platform's cost of entry is sufficiently large, the optimal information policy yields the same market outcome that is attained under the optimal entry policy. Moreover, an outright ban either on entry by imitation or data sharing, in general, may be welfare reducing as the platform adjusts its referral fee in response to such policies.

Acknowledgments

For their helpful comments and suggestions, the authors thank Joseph Harrington, Justin Johnson, Jeanine Miklós-Thal, Volker Nocke, Martin Peitz, Yossi Spiegel, Tat-How Teh, Chengsi Wang, Julian Wright, and the seminar/conference participants at IIFT (Kolkata), Michigan State University, Seoul National University, Antitrust Economics & Competition Policy Workshop at Simon Business School (University of Rochester), 20th Annual Berkeley-Columbia-Duke-MIT-Northwestern IO Theory Conference (Northwestern University), Asian Meeting of the Econometric Society, and NUS Platform Workshop Program.

Appendix A. Omitted Proofs

Proof of Proposition 1. Notice that

$$\Pi_P^{NE}(r) - \Pi_P^{NC}(r) = \int_{\theta_P(r)}^{1} r\theta d\theta \begin{cases} > 0 & \text{if } r < \overline{r} \\ = 0 & \text{otherwise,} \end{cases}$$

where $\overline{r}$ denote the value such that $\theta_P(\overline{r}) = 1$, that is, $\overline{r} = 1 - K_P/\delta$. It is immediate that $r^{NC} = r^{NE}$ if $r^{NE} \geq \overline{r}$.

Thus, it suffices to show that $r^{NC} \geq \bar{r}$: if $r^{NE} \geq \bar{r}$ then $r^{NE} = r^{NC}$, while if $r^{NE} < \bar{r}$ then $r^{NE} \leq r^{NC}$. For any $r < \bar{r}$, we have $\theta_S(r) < \theta_P(r)$ and

$$\theta_S'(r) = \frac{K}{(1-r)^2} < \theta_P'(r) = \frac{K_P}{\delta(1-r)^2},$$

where the inequality holds because of Assumption 1. Therefore,

$$\frac{d}{dr}\Pi_P^{NC}(r) = \int_{\theta_S(r)}^{\theta_P(r)} \theta d\theta + r[\theta_P'(r)\theta_P(r) - \theta_S'(r)\theta_S(r)] > 0.$$

This means that $\Pi_P^{NC}(r)$ is strictly increasing whenever $r < \bar{r}$, so $r^{NC} \geq \bar{r}$. □

Proof of Proposition 2. Since the result is immediate if $r^C < \bar{r} \leq r^{NE}$, it suffices to consider the case where $r^C, r^{NE} < \bar{r}$. At any $r < \bar{r}$, we have

$$\frac{d}{dr}(\Pi_P^C(r) - \Pi_P^{NE}(r)) = \frac{d}{dr}\int_{\theta_P(r)}^1 \alpha(\theta; r)[\delta(1-r)\theta - K_P]d\theta < 0,$$

where the inequality holds because both $\alpha(\theta;r)$ and $\delta(1-r)\theta - K_P$ are positive and decreasing in r. In other words, $\Pi_P^C(r)$ is strictly decreasing whenever $\Pi_P^{NE}(r)$ is decreasing. Since $\Pi_P^C(r)$ is quasi-concave, this implies that $r^C < r^{NE}$. □

Proof of Lemma 1. It is useful to first formally state this lemma: consider any set X of signal realizations and a (measurable) signal $\sigma : [\theta_S, 1] \to \Delta(X)$, where $\Delta(X)$ denotes the set of all probability distributions over X. There exists a binary signal $\hat{\sigma} : [\theta_S, 1] \to \Delta(\{0,1\})$ that implements the same equilibrium outcome as the signal σ.

The proof is as follows: For each x, let $\beta(x)$ denote the probability that the platform enters. Clearly, (since the platform cannot commit to its entry policy)

$$\beta(x) \begin{cases} = 0 & \text{if } \mathbb{E}[\theta|x] < \theta_P \\ \in [0,1] & \text{if } \mathbb{E}[\theta|x] = \theta_P \\ = 1 & \text{if } \mathbb{E}[\theta|x] > \theta_P. \end{cases}$$

Notice that the probability that the platform enters conditional on θ is given by

$$\widehat{\beta}(\theta) = \int \beta(x) d\sigma(\theta).$$

Consider the following binary signal: $\widehat{X} = \{0,1\}$ and for each θ, $\sigma(\theta)$ assigns probability $1 - \widehat{\beta}(\theta)$ to 0 and probability $\widehat{\beta}(\theta)$ to 1. By construction, this signal induces the same outcome, provided that the platform's obedience constraint is satisfied (i.e., $\mathbb{E}[\theta|0] \leq \theta_P$ and $\mathbb{E}[\theta|1] \geq \theta_P$). To see that this last requirement automatically holds from our construction, divide the set X as follows:

$$X_< := \{x \in X : \mathbb{E}[\theta|x] < \theta_P\},$$
$$X_= := \{x \in X : \mathbb{E}[\theta|x] = \theta_P\},$$
$$\text{and } X_> := \{x \in X : \mathbb{E}[\theta|x] > \theta_P\}.$$

By our construction, each $x \in X_<$ is mapped to 0 in our binary signal, each $x \in X_=$ is split between 0 and 1, and each $x \in X_>$ is mapped to 1. This implies that

$$\mathbb{E}[\theta|0] \leq \mathbb{E}[\theta|x \in X_< \cup X_=] \leq \theta_P \text{ and}$$
$$\mathbb{E}[\theta|0] \geq \mathbb{E}[\theta|x \in X_= \cup X_>] \geq \theta_P. \quad \square$$

Proof of Proposition 4. The proof is given by the following steps.

Step 1. Let $\phi : [0,1] \to \{0,1\}$ be the entry decision of the seller ($\phi = 1$ if the seller enters) induced by the information structure (and r). As argued in Section 5.2, we have $\Pr(x = 1|\theta) = \alpha(r, \theta)$ for all θ such that $\phi(\theta) = 1$. In addition, the platform prefers the seller to enter whenever $\theta \in [\theta_S(r), \theta_P(r)]$, as it not only yields direct benefits to the platform but also relaxes (OC_0) by raising the right-hand side in (4). This implies that the platform's problem can be written as[31]:

$$\max_{\phi(\cdot)\in\{0,1\}} \int_{\theta_P}^1 \phi(\theta)[(1-\alpha(\theta,r))r\delta\theta + \alpha(\theta)(\delta\theta - K_P)]d\theta$$
$$\text{s.t.} \int_{\theta_P}^1 \phi(\theta)(\theta - \theta_P)(1-\alpha(\theta,r))d\theta \leq \int_{\theta_S}^{\theta_P}(\theta_P - \theta)d\theta. \tag{A.1}$$

Step 2. Consider the associated Lagrangian:

$$\mathcal{L} = \int_{\theta_P}^1 \phi(\theta)[(1-\alpha(\theta))r\delta\theta + \alpha(\theta)(\delta\theta - K_P) - \lambda(\theta - \theta_P)(1-\alpha(\theta))]d\theta + \lambda\int_{\theta_S}^{\theta_P}(\theta_P - \theta)d\theta.$$

Since this is linear in $\phi(\theta)$, it is immediate that $\phi(\theta) = 1$ if

$$H(\theta, \lambda) := (1-\alpha(\theta))(r\delta\theta - \lambda(\theta - \theta_P)) + \alpha(\theta)(\delta\theta - K_P) > 0,$$

and $\phi(\theta) = 0$ if $H(\theta, \lambda) \leq 0$.

Step 3. Routine calculation yields,

$$\frac{\partial^2}{\partial\theta^2}H(\theta,\lambda) = \frac{2K}{\delta(1-r)\theta^3}(K_P + \lambda\theta_P) > 0,$$

implying that H is convex in θ. Now

$$H(\theta_P, \lambda) = (1-\alpha(\theta_P))r\delta\theta_P + \alpha(\theta_P)(\delta\theta_P - K_P)$$
$$= r\delta\theta_P + \alpha(\theta_P)(\delta(1-r)\theta_P - K_P) = r\delta\theta_P > 0.$$

Thus, if $H \leq 0$ for some θ, we have an interval $[\theta_*, \theta^*]$ where $\theta_* > \theta_P$ and $\theta^* \in [\theta^*, 1]$ such that $H \leq 0$ if and only if $\theta \in [\theta_*, \theta^*]$. And if $H > 0$ for all θ, we set $\theta_* = \theta^* = 1$. Thus, at the optimum, $\phi(\theta) = 1$ for all $\theta \in [\theta_P, \theta_*] \cup [\theta^*, 1]$ and $\phi(\theta) = 0$ for all $\theta \in [\theta_*, \theta^*]$. The signal structure (5) follows as having $x = 1$ with certainty for all $\theta \in [\theta_*, \theta^*]$ relaxes (A.1) and thwarts entry of the types in $[\theta_*, \theta^*]$. □

Appendix B. The Binary-Type Case

This appendix considers the case where the seller's type θ is either ℓ or h, where $0 < \ell < h$. We use μ to denote the probability that $\theta = h$.

We maintain the following assumptions on parameter values, which is comparable to (1) in the main model.

Assumption B.1.

(i) $(1-\delta)h < K < \ell$, *(ii)* $\delta\ell < K_P < \delta h$, *and (iii)* $K < K_P/\delta < Kh/\ell$.

The first assumption means that the seller's entry is sensitive to the platform's (expected) policy: The low-type seller may enter the platform (i.e., $K < \ell$), while (even) the high-type seller has no incentive to enter if the platform will subsequently enter and steal his business for sure (i.e., $K > (1-\delta)h$). The second assumption suggests that the platform will never enter if $\theta = \ell$, but may have an incentive to do so if $\theta = h$. The final assumption ensures that the seller, due to the first-period gain, has a stronger incentive to enter than the platform ($K < K_P/\delta$), but the platforms' incentive is also non-trivial relative to the seller's; this latter part will become clear in the subsequent analysis.

B.1. No Entry by Platform

Consider the case where P does not (or cannot) enter. In this case, the optimal r should be the level at which one of the two seller types is indifferent between entering and not doing so. For each $\theta = \{\ell, h\}$, let r_θ be the value such that

$$(1-r_\theta)\theta = K \Leftrightarrow r_\theta := 1 - \frac{K}{\theta}.$$

Then, P prefers r_ℓ to any $r < r_\ell$ (as both seller types will enter as long as $r \le r_\ell$) and r_h to any $r > r_\ell$ (as only the high type will enter if $r \in (r_\ell, r_h)$ and no type will if $r > r_h$). This implies that r_h is optimal to P if and only if

$$r_\ell((1-\mu)\ell + \mu h) \le r_h \mu h \Leftrightarrow \mu \ge \mu^{NE} := \frac{r_\ell \ell}{r_\ell \ell + (r_h - r_\ell)h}.$$

If $\mu < \mu^{NE}$ then r_ℓ is optimal.

B.2. Entry by Platform Whenever Possible (or No Commitment)

Consider the case where P enters whenever profitable (i.e., when P has no commitment power over its own entry). By (ii) in Assumption B.1, P will not enter if $\theta = \ell$. Therefore, it suffices to consider P's incentive to enter when $\theta = h$.

When $\theta = h$, P has no incentive to enter if and only if

$$\delta h - K_P \le r\delta h \Leftrightarrow r \ge r_P^{NC} := 1 - \frac{K_P}{\delta h}.$$

(iii) in Assumption B.1 ensures that[32]

$$r_\ell = 1 - \frac{K}{\ell} < r_P^{NC} = 1 - \frac{K_P}{\delta h} < r_h = 1 - \frac{K}{h}.$$

Importantly, this implies that no seller enters not only when $r > r_h$, but also when $r \in (r_\ell, r_P^{NC})$; in the latter case, the high-type seller does not enter for fear of the platform's entry.

The platform's expected profit, as a function of r, is given by

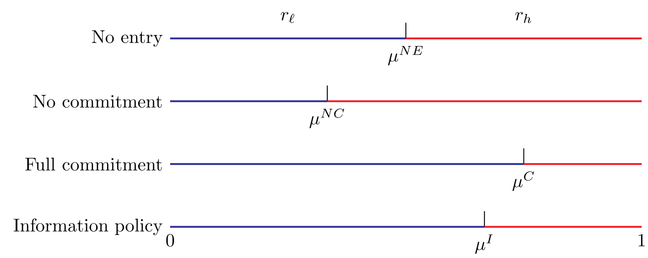
$$\Pi_P^{NC}(r) = \begin{cases} r(1-\mu)\ell & \text{if } r \le r_\ell \\ 0 & \text{if } r \in (r_\ell, r_P^{NC}) \\ r\mu h & \text{if } r \in [r_P^{NC}, r_h] \\ 0 & \text{if } r > r_h. \end{cases}$$

Since Π_P^{NC} is strictly increasing below r_ℓ and also over $(r_P^{NC}, r_h]$, it follows that r_h is optimal if and only if

$$\Pi_P^{NC}(r_\ell) = r_\ell(1-\mu)\ell \le \Pi_P^{NC}(r_h) = r_h \mu h \Leftrightarrow \mu \ge \mu^{NC} := \frac{r_\ell \ell}{r_\ell \ell + r_h h}.$$

It is easy to see that $\mu^{NE} > \mu^{NC}$, as depicted in Figure B.1. This means that if $\mu \in (\mu^{NC}, \mu^{NE})$ then P chooses r_ℓ with no entry but r_h with no commitment; otherwise, P has the same optimal referral fee in the two cases. Note that this result is consistent with Proposition 1 in Section 3; P has an incentive to raise his referral fee when he has no commitment power over entry.

Figure B.1 (Color online) This Figure Shows When r_ℓ (or r_h) Is Optimal in Each Regime



Notes. The relative positions of μ^{NE}, μ^{NC}, and μ^C are always as described, and $\mu^{NE} < \mu^I \le \mu^C$ also always holds. However, μ^I may or may not be larger than μ^{NE}, depending on (B.2).

B.3. Full Commitment to Entry

Consider the case where P can commit to its entry policy, as in Section 4. As before, it suffices to consider r_ℓ and r_h, and the latter yields $r_h \mu h$ to P. Unlike before, if $r = r_\ell$ then P can extract more surplus from the high type. In particular, P can set $r = r_\ell$ and commit to enter with probability α if $\theta = h$, where α is the value such that the high-type seller is indifferent between entering and not entering given r_ℓ, that is,[33]

$$(1-\delta\alpha)(1-r_\ell)h = K \Leftrightarrow \alpha := \frac{1}{\delta}\left(1 - \frac{K}{(1-r_\ell)h}\right) = \frac{1}{\delta}\left(1 - \frac{\ell}{h}\right).$$

By construction, the high-type seller enters, but does not receive any surplus. Therefore, this policy is optimal to P conditional on $r = r_\ell$. P's resulting expected payoff is

$$\begin{aligned}&(1-\mu)r_\ell \ell + \mu[(1-\alpha)r_\ell h + \alpha((1-\delta)r_\ell h + \delta h - K_P)] \\ &\quad = (1-\mu)r_\ell \ell + \mu[r_\ell h + \alpha(\delta(1-r_\ell)h - K_P)].\end{aligned}$$

Comparing this to $r_h \mu h$, it follows that r_h is optimal if and only if

$$\mu \ge \mu^C := \frac{r_\ell \ell}{r_\ell \ell + (h-\ell)\frac{K_P}{\delta h}}.$$

As depicted in Figure B.1, $\mu^C > \mu^{NE}$, which means that P is more likely to choose $r = r_\ell$ in the commitment case than in the no-entry case and so is consistent with Proposition 2.

B.4. Information Policy

As in Section 5, we can restrict attention to the case where P observes either 0 or 1. In addition, the commitment outcome for $\mu < \mu^C$ is implementable if and only if P has no incentive to enter conditional on observing 0, that is,

$$\delta \frac{(1-\mu)\ell + \mu(1-\alpha)h}{1-\mu+\mu(1-\alpha)} - K_P \le r_\ell \delta \frac{(1-\mu)\ell + \mu(1-\alpha)h}{1-\mu+\mu(1-\alpha)}.$$

Arranging the terms, the condition simplifies to

$$\mu \le \mu^* := \frac{\ell}{\ell + \frac{\delta h - (h-\ell)}{\delta h}\frac{\delta K h - K_P \ell}{K_P - \delta K}}.$$

Consider the case where $\mu^C \le \mu^*$, equivalently,

$$\frac{h-\ell}{r_\ell}\frac{K_P}{\delta h} \ge \frac{\delta h - (h-\ell)}{\delta h}\frac{\delta K h - K_P \ell}{K_P - \delta K}. \tag{B.1}$$

In this case, the full commitment outcome can always be implemented: If $\mu < \mu^C$ then the above obedience constraint guarantees the result. If $\mu \geq \mu^C$ then the platform's optimal referral fee is r_h with commitment, which can be trivially implemented (by setting $r = r_h$). Notice that (B.1) holds if K_P/δ is sufficiently close to Kh/ℓ and fails if K_P/δ is sufficiently close to K.

Next, consider the case where (B.1) fails, so $\mu^* < \mu^C$. In this case, for $\mu \in (\mu^*, \mu^C)$, the full commitment outcome cannot be implemented by any information policy. To determine the condition under which setting r_h is optimal (more profitable than setting $r = r_\ell$) for the platform, suppose $r = r_\ell$. In this case, it cannot be that the high-type seller enters with probability 1; if so, as explained above, the platform's obedience constraint after observing $x = 0$ would be violated. Let ϕ denote the probability that the high-type seller enters. For $\phi \in (0,1)$, the high-type seller should be indifferent between entering and not entering, which holds if and only if the platform enters with probability α conditional on $\theta = h$. This means that the optimal binary signal is the same as in the case when the full commitment outcome can be implemented (i.e., $Pr\{x = 1 | \theta = h\} = \alpha$ and $Pr\{x = 1 | \theta = \ell\} = 0$).

For the platform not to be willing to enter after observing $x = 0$, it must be that

$$\delta \frac{(1-\mu)\ell + \mu\phi(1-\alpha)h}{(1-\mu) + \mu\phi(1-\alpha)} - K_P \leq r_\ell \delta \frac{(1-\mu)\ell + \mu\phi(1-\alpha)h}{(1-\mu) + \mu\phi(1-\alpha)},$$

which can be rewritten as

$$\phi \leq \phi^* := \frac{(1-\mu)\ell(K_P - \delta K)}{\mu(1-\alpha)(\delta K h - K_P \ell)}.$$

Intuitively, since the low-type seller always enters, conditional on observing $x = 0$, the seller is less likely to be of high type, the less frequently the high-type seller enters. Therefore, the platform's obedience constraint holds when ϕ is sufficiently small.

Clearly, the platform's payoff increases in ϕ. Therefore, the platform's maximized expected payoff with $r = r_\ell$ is equal to

$$(1-\mu) r_\ell \ell + \mu\phi^* [r_\ell h + \alpha(\delta(1-r_\ell)h - K_P].$$

As in the previous cases, r_h is optimal for the platform if and only if $r_h \mu h$ is larger than this payoff, that is,

$$\mu \geq \mu^I := \frac{r_\ell \ell + \frac{\ell(K_P - \delta K)}{(1-\alpha)(\delta K h - K_P \ell)}[r_\ell h + \alpha(\delta(1-r_\ell)h - K_P)]}{r_h h + r_\ell \ell + \frac{\ell(K_P - \delta K)}{(1-\alpha)(\delta K h - K_P \ell)}[r_\ell h + \alpha(\delta(1-r_\ell)h - K_P)]}.$$

It is easy to see that, under Assumption B.1, $\mu^{NC} < \mu^I$ always holds. Although fairly cumbersome, it can be shown that $\mu^I < \mu^C$ whenever (B.1) fails. The order between μ^{NE} and μ^I is ambiguous in general. Using the closed-form solutions above, it can be shown that

$$\mu^{NE} \leq \mu^I \Longleftrightarrow \frac{r_\ell}{r_h - r_\ell} \frac{1 - \frac{K}{\ell}}{h - K - (h-\ell)\frac{K_P}{\delta h}} \leq \frac{\ell(K_P - \delta K)}{(1-\alpha)(\delta K h - K_P \ell)}. \tag{B.2}$$

This inequality necessarily fails if K_P/δ is sufficiently close to K and holds if K_P/δ is close to K.

B.5. Ban on Information Sharing

Finally, we study the case where the platform is not allowed to use proprietary data about sellers' products but there is no restriction on imitation, as in the second part of Section 6. For the same reason as in the baseline model, there never exists an equilibrium in which the platform enters with an interior probability (i.e., $\eta \in (0,1)$).

If $r = r_h$ then the platform extracts all surplus from type h and so has no incentive to enter (i.e., $\eta = 0$). If $r = r_\ell$ then there is a futile equilibrium in which the platform always enters (i.e., $\eta = 1$)—believing that the entering seller is of type h—and so the seller never enters. There may exist another equilibrium in which the platform does not enter (i.e., $\eta = 0$), and both types enter. For the platform's incentive, the equilibrium requires that

$$\delta((1-\mu)\ell + \mu h) - K_P \leq \delta r_\ell((1-\mu)\ell + \mu h)$$
$$\Longleftrightarrow \mu \leq \underline{\mu} := \frac{K_P - \delta K}{\delta K}\frac{\ell}{h - \ell}.$$

It then follows that (focusing on the more profitable equilibria with $\eta = 0$) r_ℓ is optimal if $\mu \leq \min\{\mu^{NE}, \underline{\mu}\}$, while r_h is optimal otherwise.

Of particular interest is when $\underline{\mu} < \mu^{NE}$. In that case, for $\mu \in (\underline{\mu}, \mu^{NE})$, the platform chooses $\overline{r_\ell}$ in the no entry case but r_h with a ban on data sharing. From the above closed-form expressions, it can be directly shown that

$$\underline{\mu} < \mu^{NE} \Longleftrightarrow \frac{K_P}{\delta K} < \frac{r_h h}{r_\ell \ell + (r_h - r_\ell)h}.$$

This inequality holds when K_P/δ is relatively close to K (because the right-hand side strictly exceeds 1), but fails when K_P is sufficiently large.

Appendix C. Ad Valorem Fee with Positive Marginal Cost

This appendix considers the case where the third-party seller and the platform face marginal cost c and the platform's ad valorem fee is levied on the seller's revenue. We show that both Proposition 1 and Proposition 2 continue to hold in this environment, provided that c is not particularly large.

C.1. Setup

Following the discussion at the end of Section 2, we assume that the demand function for the seller's product is given by $D(p, \theta) := \theta d(p)$. For tractability, we further assume that $d(p) = 4(1-p)$; notice that if $c = 0$ then the optimal monopoly price (maximizing $pd(p)$) is $p^m = 1/2$, and the resulting profit is $p^m d(p^m) = 1$. We extend Assumption 1 as follows:

Assumption C.1. $(1-\delta)(1-c)^2 < K$, $K_p < \delta(1-c)^2$, *and* $K < K_P/\delta$.

C.2. Optimal Pricing and Profit

Given referral fee r, the third-party seller's optimal pricing problem is given by

$$\max_p [(1-r)p - c]d(p) = [(1-r)p - c]4(1-p).$$

It can be directly shown that the seller's optimal price is

$$p_S(r) := \frac{1}{2} + \frac{c}{2(1-r)}.$$

The resulting profit is

$$\pi_S(r) := [(1-r)p_S(r) - c]d(p_S(r)) = \frac{(1-r-c)^2}{1-r}.$$

Meanwhile, the platform collects the following amount of referral fee from the seller:

$$\pi_P^R(r) := rp_S(r)d(p_S(r)) = r\left(1 - \frac{c^2}{(1-r)^2}\right).$$

If the platform enters then, because it does not incur referral costs, it faces the following optimal pricing problem:

$$\max_p (p-c)d(p) = 4(p-c)(1-p).$$

It is easy to see that the optimal price is $(1+c)/2$ and the resulting profit is

$$\pi_P^E := (1-c)^2.$$

If $c=0$ then, even if $r>0$, we have

$$\pi_S(r) + \pi_P^R(r) = (1-r) + r = \pi_P^E.$$

In other words, producer surplus—the sum of the seller's and the platform's profits—is maximized despite the presence of referral fee. If $c>0$, however,

$$\pi_S(r) + \pi_P^R(r) < \pi_P^E \Longleftrightarrow r > 0.$$

This is the usual effect of double marginalization. As shown shortly, this complicates the analysis because it is no longer the case that $\pi_S'(r) = (\pi_P^E - \pi_P^R(r))'$ and $\theta_P(r) - \theta_S(r)$ is a simple monotone function of r.

C.3. No Entry by the Platform

Suppose, as in Section 3.1, the platform never enters. Given r, the seller enters if and only if $\theta\pi_S(r) \geq K$. Then, the platform's problem is given by

$$\mathcal{P}_{NE}: \max_r \Pi_P^{NE}(r) := \int_{\theta_S(r)}^1 \pi_P^R(r)\theta d\theta,$$

where

$$\theta_S(r) := \min\left\{\frac{K}{\pi_S(r)}, 1\right\}.$$

We let r^{NE} denote the solution to $\mathcal{P}_{NE}$.

C.4. Entry by the Platform Whenever Profitable

Given r, the platform prefers to enter if and only if

$$\delta\theta\pi_P^E - K_P \geq \delta\theta\pi_P^R(r) \Longleftrightarrow \theta \geq \theta_P(r) := \min\left\{\frac{K_P}{\delta(\pi_P^E - \pi_P^R(r))}, 1\right\}.$$

As in the baseline case, Assumption C.1 implies that no seller would enter if she expects the platform to enter with probability 1 in the second period. Therefore, the platform's problem is given by

$$\mathcal{P}_{NC}: \max_r \Pi_P^{NC}(r) := \int_{\theta_S(r)}^{\theta_P(r)} \pi_P^R(r)\theta d\theta.$$

We let r^{NC} denote the solution to this problem.

C.5. Robustness of Proposition 1

We now show that $r^{NC} \geq r^{NE}$, provided that c is not particularly large. The problem is trivial if $\theta_P(r^{NE}) = 1$ or $\theta_P(r^{NE}) \leq \theta_S(r^{NE})$. So, suppose $\theta_S(r^{NE}) < \theta_P(r^{NE}) < 1$. Then, r^{NE} satisfies

$$\frac{d}{dr}\Pi_P^{NE}(r^{NE}) = \frac{d}{dr}\pi_P^R(r^{NE})\int_{\theta_S(r^{NE})}^1 \theta d\theta - \pi_P^R(r^{NE})\theta_S(r^{NE})\theta_S'(r^{NE}) = 0. \tag{C.1}$$

Consider Π_P^{NC} around r^{NE}. Then,

$$\begin{aligned}\frac{d}{dr}\Pi_P^{NC}(r^{NE}) &= \frac{d}{dr}\pi_P^R(r^{NE})\int_{\theta_S(r^{NE})}^{\theta_P(r^{NE})} \theta d\theta - \pi_P^R(r^{NE})\theta_S(r^{NE})\theta_S'(r^{NE}) \\ &\quad + \pi_P^R(r^{NE})\theta_P(r^{NE})\theta_P'(r^{NE}) \\ &= -\frac{d}{dr}\pi_P^R(r^{NE})\int_{\theta_P(r^{NE})}^1 \theta d\theta + \pi_P^R(r^{NE})\theta_P(r^{NE})\theta_P'(r^{NE}),\end{aligned}$$

where the second equality is due to (C.1).

We can conclude that $r^{NC} > r^{NE}$ if $d\Pi_P^{NC}(r^{NE})/dr > 0$. Its sufficient condition is

$$\theta_P(r^{NE})\theta_P'(r^{NE}) \geq \theta_S(r^{NE})\theta_S'(r^{NE}), \tag{C.2}$$

because the inequality implies

$$\begin{aligned}\frac{d}{dr}\Pi_P^{NC}(r^{NE}) &\geq -\frac{d}{dr}\pi_P^R(r^{NE})\int_{\theta_P(r^{NE})}^1 \theta d\theta + \pi_P^R(r^{NE})\theta_S(r^{NE})\theta_S'(r^{NE}) \\ &= \frac{d}{dr}\pi_P^R(r^{NE})\int_{\theta_S(r^{NE})}^{\theta_P(r^{NE})} \theta d\theta > 0.\end{aligned}$$

If $c=0$ then (C.2) holds with strict inequality because

$$\theta_P(r^{NE}) = \frac{K_P}{\delta(1-r^{NE})} > \theta_S(r^{NE}) = \frac{K}{1-r^{NE}} \text{ and } \theta_P'(r^{NE}) > \theta_S'(r^{NE}).$$

Since both θ_S and θ_P are continuous in c, (C.2) necessarily holds for c sufficiently small.

C.6. Full Commitment to Entry

Next, consider the case where the platform has full commitment power over its own entry policy. Just as in Section 4, given r, it is optimal for the platform to enter with the following probability for each $\theta > \theta_P(r)$:

$$\alpha(\theta; r) := \frac{1}{\delta}\left(1 - \frac{K}{\pi_S(r)}\right).$$

Therefore, the platform's problem reduces to

$$\begin{aligned}&\mathcal{P}_C: \max_{r\in[0,1]} \Pi_P^C(r) \\ &:= \int_{\theta_S(r)}^{\theta_P(r)} \pi_P^R(r)\theta d\theta + \int_{\theta_P(r)}^1 \left[\begin{array}{c}(1-\delta)\pi_P^R(r)\theta + \\ [\alpha(\theta;r)(\delta\pi_P^E\theta - K_P) + (1-\alpha(\theta;r))\delta\pi_P^R(r)\theta]\end{array}\right] d\theta.\end{aligned}$$

C.7. Robustness of Proposition 2

Again, it suffices to consider the case where $\theta_P(r^{NE}) < 1$. In that case,

$$\Pi_P^C(r) - \Pi_P^{NE}(r) = \int_{\theta_P(r)}^1 \alpha(\theta; r)[\delta(\pi_P^E - \pi_P^R(r))\theta - K_P]d\theta.$$

It suffices to show that this expression is decreasing at r^{NE}, for which it is sufficient that π_P^R is increasing at r^{NE}: since $\pi_S(r)$ is necessarily decreasing in r, $\alpha(\theta; r)$ is also decreasing. Therefore, as long as $\pi_P^R(r)$ is decreasing at r^{NE}, we have

$$\begin{aligned}&\frac{d}{dr}(\Pi_P^C(r^{NE}) - \Pi_P^{NE}(r^{NE})) \\ &= \int_{\theta_P(r)}^1 \frac{d}{dr}\alpha(\theta; r^{NE})[\delta(\pi_P^E - \pi_P^R(r^{NE}))\theta - K_P]d\theta < 0.\end{aligned}$$

From the solution of $\pi_P^R(r)$ above, it can be directly shown that given $r^{NE}(<1-c)$, $\pi_P^R(r)$ is strictly increasing around r^{NE}, provided that c is sufficiently small. In other words, if $c=0$ then $\pi_P^R(r)=r$, which is linear. A small perturbation of c can have only a marginal effect on the slope of π_P^R at r^{NE}.

Endnotes

[1] The rapid increase in the availability of product variety and expansion of market share of niche products with the emergence of online retailers is often referred to as the "long tail" effect (Anderson 2006), and has been explored by several scholars in both economics and management literature (Brynjolfsson et al. 2011, Yang 2013, Goldfarb and Tucker 2019).

[2] To quote Margrethe Vestager, European Competition Commissioner and Vice-President of the European Commission, "the decisions that gatekeepers take, about how to rank different companies in search results, can make or break businesses in dozens of markets that depend on the platform. And if platforms also compete in those markets themselves, they can use their position as player and referee to help their own services succeed, at the expense of their rivals." (Speech by Executive Vice-President Margrethe Vestager: Building trust in technology, October 29, 2020; available at: https://ec.europa.eu/commission/presscorner/detail/en/speech_20_3031.)

[3] The term was coined in early 2000 when Apple updated its own app "Sherlock," a search tool on its desktop operating system, to subsume all features that a third-party app named "Watson" was offering on its platform.

[4] As the platforms face a sequence of overlapping generations of third-party sellers, intertemporal price discrimination is difficult to implement. If the platform were to charge different fees to the sellers based on how long they have been active on the platform, existing firms might have an incentive to re-enter the market as "new" firms through simple name changes. Thus, platforms have little option but to charge consistent referral fees over time, which limits such opportunistic behavior of the third-party sellers. For example, Apple applies a standard 30 percent commission rate for App Store transactions and regular subscriptions (with very limited exceptions). Similarly, Amazon's fees are generally time-invariant and only vary by product categories.

[5] For example, when Apple allegedly "Sherlocked" Watson, it did not develop a new app by copying Watson's, but updated one of its existing tools (named "Sherlock") to offer the same functionality that Watson offered. Such possibility of "inventing around" may pose a challenge in enforcing the platform's commitment to its entry decision due to ex-post verifiability of imitation.

[6] Amazon Inc., for example, claims to share only such aggregate information so as to ensure the third-party sellers that the platform's product division would not have the necessary information on any specific seller's product that it needs to directly compete with the seller (Mattioli 2020).

[7] For a recent survey of data markets, see Bergemann and Bonatti (2019).

[8] See https://www.economist.com/by-invitation/2024/06/04/a-whack-a-mole-approach-to-big-tech-wont-do-says-europes-antitrust-chief.

[9] See the European Commission Press Release "Antitrust: Commission fines Google €4.34 billion for illegal practices regarding Android mobile devices to strengthen dominance of Google's search engine," released on July 18, 2018. Available at http://europa.eu/rapid/press-release_IP-18-4581_en.htm.

[10] See Kastrenakes and Brandom (2018) for more details.

[11] Platforms in dual mode are also called "hybrid platforms" (Anderson and Bedre-Defolie 2024), "Hybrid marketplaces" (Etro 2023) or "retailer-led marketplaces" (Hervas-Drane and Shelegia 2025). For papers that study the choice of business models, but without the possibility of dual mode, see Hagiu and Wright (2015, 2019) and Johnson (2017).

[12] We envision a situation with so many potential products that platforms are not expected to possess information about each individual product's market demand and it is not in the interest of the platform to sell a product without first observing its demand through a marketplace. Jiang et al. (2011) consider a setup similar to ours, where the platform uses third-party sellers' sales information to inform its entry decision.

[13] We do not consider any time discounting.

[14] Our assumption of zero marginal cost (along with high fixed cost of entry) closely reflects the sellers' cost structures in platforms for software applications where the "Sherlocking" behavior is well-documented.

[15] The assumption that the platform, following entry, does not face any competition from the seller is not essential for our findings but it significantly enhances the algebraic tractability of our analysis. Note that "Sherlocking" is a relevant strategy for the platform only when it can capture a large part of the sellers' profits to cover its entry cost. Our assumption of extreme self-preferencing by the platform represents this idea in its simplest form. See Section 7 for further discussion on this assumption.

[16] This assumption can be partially relaxed as all subsequent results continue to hold as long as $(1-\delta)(1-r^C)\theta - K < 0$ where r^C is the optimal referral fee defined in Section 4.

[17] If $K_P \geq \delta$ then the platform never enters, so "Sherlocking" becomes irrelevant. And if $K \geq K_P/\delta$ then the platform's Sherlocking incentive becomes too strong; it wishes to steal every entering seller's business.

[18] See Madsen and Vellodi (2025) for additional discussion on the justification of the stationary fee.

[19] If the last inequality of Assumption 1 fails (i.e., $K \geq K_P/\delta$) then $\theta_S(r) \geq \theta_P(r)$, in which case the market completely breaks down: The seller's entry will always be followed by the platform's entry, so no seller would enter.

[20] This observation is reminiscent of the "Arrow Replacement effect" (Arrow 1962), namely, that a monopolist has a weaker incentive to innovate for fear of cannibalizing her current products.

[21] In other words, the integrand $(1-\alpha)r\theta + \alpha((1-\delta)r\theta + \delta\theta - K_P)$ is increasing in α if and only if $\theta \geq \theta_P$.

[22] The structure of the optimal signal in Proposition 4 is novel to the literature. In most Bayesian persuasion problems, the optimal signal takes a simple cutoff or, more generally, monotone structure (see, e.g., Dworczak and Martini (2019) and Kleiner et al. (2021)). Pooling two disjoint intervals can be optimal if the sender communicates with an imperfectly informed receiver and their signals are correlated (see Guo and Shmaya (2019) and Kim et al. (2024)). Our characterization shows that even in a natural economic environment (without correlated information) the optimal signal may still call for such a nuanced form.

[23] For a simpler case of binary types of sellers, one could indeed show that $r^I \geq r^C$ always holds. See Appendix B.

[24] We consider information design by the platform as the default case since it is the main focus of our analysis and, as mentioned earlier, hybrid platforms often claim to filter information while sharing data between marketplace and product divisions (e.g., through aggregation by product categories). Moreover, the observed practice of "Sherlocking" also supports this choice—our analysis suggests that under some alternative benchmarks, for example, if the platform enters whenever profitable (Section 3.2), "Sherlocking" would not occur at all. Nevertheless, all subsequent discussions can be adjusted in a fairly straightforward manner when the other regime is used as a benchmark. For example,

relative to the no-commitment case in Section 3.2, prohibition on imitating the third-party sellers' products makes all participants better off.

[25] For the tractable binary-type case, the optimal referral fees can be obtained in closed form, so we can provide a necessary and sufficient condition for $r^{NE} \geq r^{I}$. See Appendix B.

[26] One may wonder whether there exists an equilibrium where the platform enters with probability $\eta \in (0,1)$. The answer is negative. For such a mixed strategy equilibrium to exist, the platform should be indifferent between entering and not entering, that is, $E[\theta|\theta \geq \theta_S(r,\eta)] = \theta_P(r)$. But this equality cannot hold whenever $r < \underline{r}$. From (7) and (8) it follows that for any such r we would have $\mathbb{E}[\theta|\theta \geq \theta_S(r,0)] > \theta_P(r)$ and, since $\theta_S(r,\eta)$ is increasing in η, for all $\eta > 0$, we have $\mathbb{E}[\theta|\theta \geq \theta_S(r,\eta)] > \mathbb{E}[\theta|\theta \geq \theta_S(r,0)] > \theta_P(r)$.

[27] See https://www.reuters.com/technology/amazon-offers-share-data-boost-rivals-dodge-eu-antitrust-fines-sources-2022-06-13/.

[28] This may be the reason why such information sharing was not included in Amazon's commitments which were accepted by the European Commission on December 20, 2022 (https://ec.europa.eu/commission/presscorner/detail/en/ip_22_7777).

[29] As a channel of self-preferencing, we can imagine a situation in which consumers make purchase decisions based on the platform's recommendations. For instance, Amazon's Buy Box features a default seller and according to one estimate (Juul 2021), over 80% of Amazon sales take place through the Buy Box. In addition, academic research shows that the Amazon platform substantially prioritizes its own private label products and third party offers shipped by its fulfillment arm, in the algorithm that determines which products are featured in its Buy Box (Raval 2022). Farronato et al. (2023) also find that Amazon-branded products are ranked higher than observably similar products in consumer research results. For a theoretical treatment of self-preferencing and the effect of regulations on search neutrality, see Zou and Zhou (2023).

[30] For an analysis of the platform's incentives to promote competition and limit the sellers' market power (as opposed to fully "expropriating" them), see Teh (2022) and Johnson et al. (2023).

[31] To simplify notation, we do not explicitly note the dependency of θ_P, θ_S, and $\alpha(\theta)$ on r.

[32] It can be shown that if $r_\ell > r_P^{NC} \Longleftrightarrow Kh/\ell < K_P/\delta$ then the platform's incentive to enter becomes irrelevant, so r_h is optimal if and only if $\mu \geq \mu^{NE}$, as in Section B.1.

[33] Under Assumption B.1, α is well defined in (0, 1) because

$$\alpha = \frac{1}{\delta}\left(1 - \frac{\ell}{h}\right) < 1 \Longleftrightarrow 1 - \delta < \frac{\ell}{h}$$

and

$$(1-\delta)h < K = (1 - r_\ell)\ell \Rightarrow (1-\delta) < (1 - r_\ell)\frac{\ell}{h} < \frac{\ell}{h}.$$

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