Self-Preferencing and Welfare in Hybrid Marketplaces[*]

Bo Hu[†] Hongzhe Huang[‡] Zonglai Kou[§] Makoto Watanabe[¶]

September 5, 2025

Abstract

Regulatory efforts to ban *self-preferencing*—the practice of hybrid platforms favoring their own products—are gaining traction. Our model reveals that this practice is not purely a tactic to exclude competitors; instead, platforms use it strategically to manage excessive entry of third-party sellers. We show that an outright ban can backfire. By forcing the platform to use a blunter instrument—high commission fees—a ban may over-deter seller entry, ultimately harming consumers and reducing social welfare. The negative welfare outcome can occur under both a large and a small first-party presence.

Keywords: *Hybrid Platforms*, *Self-Preferencing*, *Seller Entry*, *Commission Fee*

[*]Hu acknowledges the financial supports from the Natural Science Foundation of China (72003041), the Shanghai Pujiang Program (21PJC011), and Shanghai Institute of International Finance and Economics; Kou acknowledges the financial support from the National Social Science Fund of China (22AZD031).

[†]Institute of World Economy, Fudan University; hu_bo@fudan.edu.cn.

[‡]School of Economics, Fudan University; 23110680035@m.fudan.edu.cn

[§]School of Economics and Research Institute of Innovation and Digital Economy (RIDE), Fudan University; zlkou@fudan.edu.cn.

[¶]KIER, Kyoto University; makoto.wtnb@gmail.com.

1 Introduction

The business practices of retail giants like Amazon and JD.com are at the center of a global regulatory debate. These firms operate as hybrid platforms: they sell their own first-party products while also running a marketplace for third-party vendors. This dual role creates a sharp conflict of interest, as a platform that competes with the sellers it hosts has a great incentive to favor its own products—a practice known as "self-preferencing". However, the platform's strategic choice is not straightforward. While its own direct sales can be more profitable, the platform's retail capacity is limited. It is therefore critically dependent on third-party sellers to expand product listings and generate the trading volume essential to its success. Yet, these same sellers introduce a cannibalization risk, threatening to crowd out the platform's lucrative first-party sales.

This tension raises critical questions: From the platform's perspective, under what conditions is it actually profit-maximizing to engage in self-preferencing? From a regulatory perspective, what are the welfare implications for consumers and the market as a whole? Banning self-preferencing may seem like a straightforward pro-competitive policy, but how do platforms react to such a ban?

To answer these questions, this paper develops a framework of hybrid intermediation. We model a platform managing its marketplace with two distinct instruments: a percentage commission fee and a direct curation tool that limits which third-party sellers are displayed to buyers. We find that the platform does not self-preference by default. Instead, it deploys curation as a strategic response only when facing "excessive entry"—a situation where the number of sellers attracted by its revenue-maximizing commission rate is higher than its profit-maximizing level. This scenario is most likely to arise when the platform's own first-party retail presence is large, total market demand is low, or seller entry costs are low.

When self-preferencing is employed, it allows the platform to decouple two distinct objectives: the platform sets its commission rate to maximize per-transaction revenue while using curation to fine-tune seller quantity to its ideal level. Under a regulatory ban, the platform must then resort to the blunt instrument of high commission fees to deter entry. This single lever is less efficient and can lead to a surprising "over-deterrence" effect: the high fees can discourage entry so severely that the final number of sellers is even lower than what the platform would have chosen to display if self-preferencing were allowed.

Our welfare analysis reveals that a regulatory ban on self-preferencing has ambiguous, and sometimes negative, welfare consequences. While self-preferencing can be used to foreclose third-party sellers, it can also be a tool to correct for excessive entry, bringing the number of sellers closer to the social optimum. We show that a ban can harm social welfare under two distinct scenarios, which depend on the interplay between the platform's profit motives and its first-party market share. In one case, the platform is prone to listing too many third-party sellers relative to the social optimum. Then, if the platform's first-party presence is small, a ban would lead to even more sellers on the platform. In the other case, the platform is prone to listing too few sellers. Then, if the first-party presence is large, a ban triggers the over-deterrence response, resulting in even fewer sellers entering. In both scenarios, a ban pushes the market equilibrium further away from the social optimum, and this negative effect, combined with the distortions caused by commission fees, makes self-preferencing the more welfare-friendly option.

We also consider whether a lump-sum participation fee could substitute for self-preferencing. We find that the lump sum fee is not only a perfect substitute for achieving a target number of sellers but also a superior instrument from both a profit and welfare perspective. Self-preferencing is wasteful because some sellers incur entry costs but are ultimately never displayed to buyers. A participation fee, in contrast, is an efficient transfer that ensures only the desired number of sellers enter in the first place. The superiority of fees suggests that the real-world prevalence of self-preferencing may stem from practical or contractual barriers that prevent platforms from implementing direct entry pricing (see discussions, e.g., Wang and Wright 2017).

These results carry important policy implications. They suggest that regulatory efforts focused solely on banning self-preferencing are incomplete. Instead of a simple prohibition, which could trigger an inefficient over-deterrence response, a more effective approach would be to incentivize platforms to adopt transparent and efficient fee structures for managing marketplace access, such as explicit participation fees. By nudging platforms away from wasteful curation practices and toward direct pricing instruments, policymakers could mitigate the social costs of entry without compromising platforms' ability to manage seller populations, potentially leading to a more efficient market outcome for all participants.

Related Literature

Our paper contributes to the recent and active literature on platform self-preferencing (e.g., de Cornière and Taylor 2019; Zennyo 2022; Gautier, Hu and Watanabe 2023; Anderson and Defolie 2024; Dendorfer 2024; Sato and Kittaka 2024; Chi, Choi, Hahn and Kim 2025; Hervas-Drane and Shelegia 2025). Our primary contribution is to develop a richer theoretical framework that reveals when and why platforms choose to self-preference. To do this, we construct a model that jointly considers the platform's use of *a continuous degree of self-preferencing*, *a variable scale for its own first-party presence*, and *the pricing friction of double marginalization*. Crucially, we analyze these decisions in a market with free entry of sellers—an element that is largely absent in other studies. This integrated framework enables us to uncover our central finding: self-preferencing is not a blanket strategy but an endogenous response to manage "excessive entry" from third-party sellers. This highlights a novel trade-off where the platform's curation and pricing decisions are jointly determined by the need to balance commission revenue against competitive pressure.

Our model provides a more nuanced perspective on the welfare effects of self-preferencing and carries important policy implications. While we concur with prior work (Zennyo 2022; Chi, Choi, Hahn and Kim 2025) that self-preferencing can lead to lower commission fees, we challenge the conclusion that it is uniformly pro-consumer. Our key distinction is the identification of a new market failure: when stripped of its ability to self-preference, a platform may resort to the blunt instrument of inefficiently high commission fees to control entry. In this context, self-preferencing can emerge as a tool that mitigates this price distortion by allowing for a lower, more efficient commission rate. This connects our work to the broader literature on excessive seller entry (Mankiw and Whinston 1986; Anderson, De Palma and Nesterov 1995; Chen and Zhang 2018; Tan and Zhou 2021), showing how a platform's curation can manage the trade-off between variety and crowding out valuable first-party sales.

Finally, our framework clarifies the role of commitment power. In contrast to Dendorfer (2024), who finds that a lack of commitment can trap a platform in a suboptimal equilibrium, our model does not suffer from time-inconsistency. In our framework, the platform's ex-ante and ex-post incentives are aligned, meaning self-preferencing is chosen if and only if it is part of the unconstrained, profit-maximizing solution.

2 A Basic Model of Hybrid Intermediation

2.1 Set-ups

Consider a large economy with a fixed measure b of buyers and an endogenous measure $s \in [0, \bar{s}]$ of third-party sellers. $\bar{s}$ is the total measure of potential sellers and is sufficiently large. s is determined by a free entry condition with each seller (incurring) a cost of entry $k > 0$. There is a homogeneous good. Each buyer has a demand for the good. Each seller can produce the good at constant cost c.

There is a platform that serves as the exclusive venue for trade. The platform hosts third-party sellers and charges a percentage fee $\gamma \in (0,1)$ on their sales revenue. The platform also acts as a retailer, owning a measure $h > 0$ of first-party sellers. We take h as an exogenous parameter. h represents the first-party capacity of the platform. Each of the h first-party sellers can also produce the good at constant marginal cost c. Thus, the platform of our model is a hybrid of third-party and first-party sales.

Matching between buyers and sellers is governed by a standard matching function $M(b, s+h)$, which yields the total measure of successful matches given b buyers and a total of $s+h$ sellers. We assume $M(\cdot)$ is strictly increasing, concave in both arguments, and exhibits constant returns to scale. Let the matching probability for each seller be $\mu^s\left(\frac{b}{s+h}\right) \equiv \frac{M(b,s+h)}{s+h}$.

While we proceed with the language of a homogeneous good for tractability, this matching technology can be micro-founded in a setting with *product differentiation*. For instance, consider a market where sellers offer distinct product variants and buyers have specific tastes. The platform's recommendation engine first identifies the subset of sellers whose offerings match a buyer's request. The function $M(\cdot)$ then represents the process of the platform recommending a single seller to the buyer from this relevant set. This crucial recommendation role, exemplified by Amazon's *Buy Box*, resolves the competition among sellers of near-identical products. In Appendix B, we formalize this interpretation and show how it gives rise to an aggregate matching function with the aforementioned properties.

The timing of the game is as follows: First, the platform announces the commission rate γ. Observing γ and the platform's first-party capacity h, potential third-party sellers simultaneously decide whether to enter the market. Finally, buyers and sellers (both first- and third-party) participate in the platform matching process. Once matched with a buyer, the seller sets price p, and the buyer has a demand of $D(p)$. The solution concept is Subgame Perfect Nash Equilibrium.

2.2 Equilibrium

We solve the model by working backward from the final stage, beginning with the sellers' pricing decisions after a successful match with a buyer. Consider the pricing problem of a first-party seller. Since this seller acts as a monopolist for a given match, it chooses a price to maximize its profit, leading to the following maximized profit:

$$\pi_m = \max_p (p - c)D(p). \tag{1}$$

Consider the pricing problem of a third-party seller. Taking commission rate γ as given, the maximized profit, denoted by $\pi_{ss}(\gamma)$, is

$$\pi_{ss}(\gamma) = \max_p [p(1-\gamma) - c]D(p). \tag{2}$$

Intuitively, the profit-maximizing price for a third-party seller, denoted by $p_s(\gamma)$, is a decreasing function of γ. From each successful third-party transaction, the platform extracts a revenue of

$$\pi_{sm}(\gamma) = \gamma p_s(\gamma)D(p_s(\gamma)). \tag{3}$$

There are two observations. First, the effect of the commission rate γ on the platform's revenue is determined by two opposing forces. On one hand, as γ increases, the platform extracts a larger share of the sales revenue. On the other hand, a higher γ effectively increases the seller's marginal cost, causing them to raise their price. This, in turn, reduces buyer demand and may decrease the total sales revenue $p_s(\gamma)D(p_s(\gamma))$. In the following, we assume the demand $D(p)$ is such that the revenue function $\gamma p_s(\gamma)D(p_s(\gamma))$ is single-peaked in γ. This assumption allows us to define $\hat{\gamma}$ as the rate that maximizes the platform's per-match fee revenue:

$$\hat{\gamma} \equiv \arg\max_\gamma \gamma p_s(\gamma)D(p_s(\gamma)). \tag{4}$$

The entry of sellers. The free-entry condition dictates that sellers will enter the platform until the expected net profit is driven to zero. Given the first-party capacity h and commission rate γ, the equilibrium mass of third-party sellers, denoted by $s_0(\gamma)$, is determined by

$$\mu^s \left(\frac{b}{s+h} \right) \pi_{ss}(\gamma) = k, \tag{5}$$

where the left-hand side is the expected profit of third-party sellers entering the platform and k is the entry cost. Since the sellers' profits $\pi_{ss}(\gamma)$ decrease as γ increases, it naturally follows that the number of sellers participating will also decrease

$$\frac{\partial s_0(\gamma)}{\partial \gamma} < 0.$$

Platform profit maximization. The platform chooses its commission fee γ to maximize total profits subject to the free-entry condition:

$$\max_{\gamma \in [0,1]} \mu^s \left(\frac{b}{h+s} \right) \Big(h\pi_m + s\pi_{sm}(\gamma) \Big), \text{ s.t. } s = s_0(\gamma),$$

where the objective is the sum of revenues from the platform's first-party and third-party sales. The choice of γ affects this profit in two ways: it *directly* influences the revenue extracted from each third-party seller, $\pi_{sm}(\gamma)$, and it *indirectly* determines the equilibrium number of sellers who enter the market, $s_0(\gamma)$.

To build intuition, we proceed in two steps. First, we solve a hypothetical, unconstrained problem where the platform can directly choose the measure of third-party sellers, s, to maximize its profit. Second, we solve the full, constrained problem in which s is endogenously determined by the sellers' free-entry condition. There we can see how the platform must adapt its strategy in response to equilibrium entry.

2.2.1 The unconstrained platform problem

In the unconstrained problem, since γ only appears in the third-party profit term $\pi_{sm}(\gamma)$, the optimal commission is simply the value $\hat{\gamma}$ that maximizes $\pi_{sm}(\gamma)$. For any given γ, the platform's problem over s is then to maximize the total number of matches multiplied by its average profit per match:

$$\max_s \; M(b, h+s) \left(\frac{h}{h+s}\pi_m + \frac{s}{h+s}\pi_{sm}(\gamma) \right)$$

Here we have rewritten the platform profits in a slightly different way. $M(b, h+s)$ is the total volume of sales, while the term in parentheses represents the average profit per match.

An increase in s creates two opposing effects on platform profits: (1) A positive *matching effect*, which increases profit by increasing the total number of sales, $M_s(\cdot) > 0$; (2) A negative *weighting effect*. Since first-party sales are more profitable for the platform ($\pi_m > \pi_{sm}$ for all γ), an increase in s shifts the sales mix toward less profitable third-party sellers, thus lowering the average profit per match.

This trade-off implies a unique, interior optimum if the profit function is well-behaved. Specifically, we require that the platform profit is single-peaked in s. A sufficient condition for this is that the elasticity of the matching function, $\varepsilon_M(s) \equiv \frac{\partial M}{\partial(h+s)} \frac{h+s}{M}$, decreases sufficiently fast in s.[1]

Lemma 1 *Assume that the platform's profits are single-peaked with respect to s. Let $\hat{s}(\gamma)$ denote the*

[1] If $\varepsilon'_M(s) < -\frac{h\left(\frac{\pi_m}{\pi_{sm}(\hat{\gamma})} - 1\right)}{\left(h\frac{\pi_m}{\pi_{sm}(\hat{\gamma})} + s\right)^2} < 0$, then the platform profit is single-peaked with respect to s.

unique profit-maximizing measure of third-party sellers. Then, $\hat{s}(\gamma)$ is single-peaked in γ. When $\hat{s}(\gamma)$ is interior, it is increasing for $\gamma < \hat{\gamma}$ and decreasing for $\gamma > \hat{\gamma}$.

The intuition for why $\hat{s}(\gamma)$ is single-peaked in γ is straightforward. The ideal number of sellers, $\hat{s}(\gamma)$, is monotonically increasing with the profit the platform earns from each third-party seller, $\pi_{sm}(\gamma)$. A higher per-seller profit shrinks the margin between first-party and third-party sales, diminishing the negative weighting effect. As this downside weakens, the platform's optimal response is to add more sellers to capitalize on the matching effect. Given this, the shape of $\hat{s}(\gamma)$ with respect to γ directly mirrors the shape of $\pi_{sm}(\gamma)$, which is assumed to be single-peaked and maximized at $\hat{\gamma}$. Combining these results gives the solution to the unconstrained platform problem:

$$(\gamma^*, s^*) = (\hat{\gamma}, \hat{s}(\hat{\gamma})).$$

2.2.2 The constrained problem with free entry of sellers

We now reintroduce the free-entry constraint, $s = s_0(\gamma)$, which makes the number of sellers an endogenous outcome of the platform's fee choice. The platform's problem reduces to choosing the commission γ to maximize its profit, now a function of γ alone:

$$\Pi_{nsp}(\gamma) = M\left(b,\ h + s_0(\gamma)\right)\left(\frac{h}{h + s_0(\gamma)}\pi_m + \frac{s_0(\gamma)}{h + s_0(\gamma)}\pi_{sm}(\gamma)\right)$$

Since the platform can no longer choose s directly, it must set a fee γ that may deviate from the unconstrained optimum, $\hat{\gamma}$, to steer seller entry towards its preferred level. This trade-off is captured by the first-order condition for the optimal fee, γ_{nsp}, which states that the marginal effects of changing γ must balance to zero:

$$\left.\frac{d\Pi_{nsp}}{d\gamma}\right|_{\gamma=\gamma_{nsp}} = \left.\underbrace{\frac{\partial \Pi_{nsp}}{\partial \pi_{sm}}\frac{\partial \pi_{sm}(\gamma)}{\partial \gamma}}_{\text{revenue effect}} + \underbrace{\frac{\partial \Pi_{nsp}}{\partial s_0}\frac{\partial s_0(\gamma)}{\partial \gamma}}_{\text{entry effect}}\right|_{\gamma=\gamma_{nsp}} = 0$$

The *revenue effect* captures how a change in γ affects the per-seller profit, $\pi_{sm}(\gamma)$. As previously shown, this effect is positive for $\gamma < \hat{\gamma}$ and negative for $\gamma > \hat{\gamma}$. The *entry effect* captures how the resulting change in seller entry, $s_0(\gamma)$, impacts total profit. This effect is a product of two terms: how the fee affects entry ($\frac{\partial s_0}{\partial \gamma} < 0$, since higher fees deter entry), and whether the platform benefits from more or fewer sellers at the margin ($\frac{\partial \Pi_{nsp}}{\partial s_0}$). The sign of the latter term depends on whether the positive matching effect or the negative weighting effect dominates.

To build intuition, consider the platform's choice at the unconstrained optimum, $\gamma = \hat{\gamma}$. At

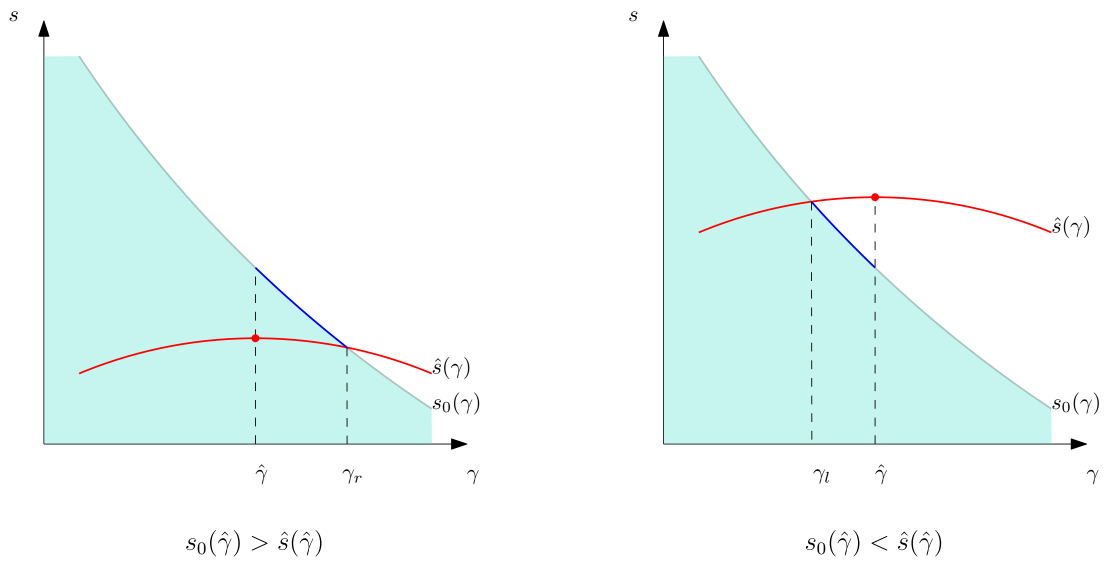

Figure 1: Optimal constrained fee under excessive entry (left) and insufficient entry (right).

this point, the revenue effect is zero, so the platform's incentive to adjust its fee is driven entirely by the entry effect. If, at $\gamma = \hat{\gamma}$, the platform suffers from *excessive entry* (i.e., $s_0(\hat{\gamma}) > \hat{s}(\hat{\gamma})$), the negative weighting effect dominates ($\frac{\partial \Pi_{nsp}}{\partial s_0} < 0$). The platform will then have an incentive to increase its fee ($\gamma_{nsp} > \hat{\gamma}$), sacrificing per-seller profit to drive out sellers and improve the average profit per match. If, at $\gamma = \hat{\gamma}$, the platform faces *insufficient entry* (i.e., $s_0(\hat{\gamma}) < \hat{s}(\hat{\gamma})$), the positive matching effect dominates ($\frac{\partial \Pi_{nsp}}{\partial s_0} > 0$). The platform will then be better off lowering its fee ($\gamma_{nsp} < \hat{\gamma}$), accepting a lower per-seller profit to attract more sellers and increase total sales volume.

This logic implies that the optimal fee is bounded. The platform will adjust its fee to manage entry, but never so much that it overcorrects. These strategic boundaries, which we denote γ_l and γ_r, are defined by the points where the free-entry supply of sellers equals the platform's ideal number, i.e., where $s_0(\gamma) = \hat{s}(\gamma)$.[2]

Proposition 1 (Optimal γ under No-Self-Preferencing) *The platform's optimal fee in the no-self-preferencing case, γ_{nsp}, is bounded by the thresholds γ_l and γ_r. If $s_0(\hat{\gamma}) > \hat{s}(\hat{\gamma})$ (excessive entry), $\gamma_{nsp} \in (\hat{\gamma}, \gamma_r]$. If $s_0(\hat{\gamma}) < \hat{s}(\hat{\gamma})$ (insufficient entry), $\gamma_{nsp} \in [\gamma_l, \hat{\gamma})$.*

Figure 1 illustrates this result. The downward-sloping gray curve shows the number of sell-

[2]Formally, the thresholds are defined as follows. The upper threshold is $\gamma_r = \min(\{\gamma \in (\hat{\gamma}, 1] \mid s_0(\gamma) = \hat{s}(\gamma)\} \cup \{1\})$. This means γ_r is the smallest solution to the equation in the specified range, or 1 if no solution exists. The lower threshold, γ_l, is defined as the solution to $s_0(\gamma) = \hat{s}(\gamma)$ for $\gamma \in [0, \hat{\gamma})$; if no such solution exists, we set $\gamma_l = 0$.

ers entering the market, $s_0(\gamma)$, while the single-peaked red curve shows the platform's unconstrained number of sellers, $\hat{s}(\gamma)$. The optimal fee, γ_c, must lie within the shaded blue section. The left panel depicts excessive entry at the unconstrained optimal fee. The platform raises its fee above $\hat{\gamma}$ to reduce the number of sellers, but not beyond the threshold γ_r, where it would over-deter entry. The optimal fee must therefore lie in $(\hat{\gamma}, \gamma_r]$. The right panel depicts insufficient entry. The platform lowers its fee below $\hat{\gamma}$ to attract sellers, but not below γ_l, where it would attract too many. The optimal fee must therefore lie in $[\gamma_l, \hat{\gamma})$.

3 Self-Preferencing

In this section, we introduce the platform's ability to engage in self-preferencing. The key difference from the model of the previous section is that the platform now has a *second, more direct instrument* to manage third-party participation. Previously, the commission rate (γ) was a blunt tool used to influence both per-seller revenue and the equilibrium number of entrants. Now, the platform can use self-preferencing to directly control the number of displayed third-party sellers, allowing it to manage market composition more precisely.

3.1 Modeling self-preferencing

We model self-preferencing as the platform's choice over the mass of third-party sellers allowed to participate in the matching process. Let s_E be the measure of third-party sellers who enter the market. The platform then chooses $s_D \leq s_E$ of these sellers to make visible, or "display," to buyers. This curation decision alters the free-entry condition. For a potential entrant, the expected profit is now the profit earned if displayed, multiplied by the probability of being displayed. This yields the new equilibrium condition for the mass of entered sellers, s_E:

$$\mu^s \left(\frac{b}{h + s_D} \right) \pi_{ss}(\gamma) \cdot \frac{s_D}{s_E} = k. \tag{6}$$

From this condition, it is straightforward to see that choosing a mass of sellers s_D from a pool s_E is equivalent to a probabilistic approach where each entrant is given a probability of being displayed equal to $\frac{s_D}{s_E}$.

The following lemma establishes the relationship between the number of displayed sellers (s_D), entered sellers (s_E), and the entry level from our benchmark model ($s_0(\gamma)$).

Lemma 2 *For any given commission rate γ, the number of displayed and entered sellers satisfies $s_D \leq$*

$s_E \leq s_0(\gamma)$. *Furthermore,* $s_E = s_0(\gamma)$ *if and only if* $s_D = s_0(\gamma)$.

The lemma reveals two insights. First, the ability to curate the marketplace chills entry. Anticipating a probability of not being displayed, fewer sellers enter than in the benchmark case $s_E \leq s_0(\gamma)$. Second, it defines the platform's new choice set. The platform now has a direct instrument s_D, but its choice is constrained by the benchmark entry level $s_D < s_0(\gamma)$.

Discussion of the modeling. Our model focuses on platform-controlled visibility. We thus set aside an important pricing channel where a higher commission γ might be passed through to consumers as a higher third-party price, potentially diverting demand to the platform's own first-party offerings, see e.g., Anderson and Defolie (2024). The analytical merit of this simplification is that it allows a clean isolation of the search and curation channel, where the platform directly manages which (set of) sellers buyers discover. This focus is reasonable and grounded in the operations of many dominant platforms where competition for visibility precedes and often outweighs direct price wars.

Consider the example of Amazon's Buy Box. On a typical Amazon product page, over 80% of sales go through the "Buy Box" — the default "Add to Cart" option. Winning the Buy Box is therefore the primary battle for sellers of the same product. While price is a factor, Amazon's proprietary algorithm awards the Buy Box based on a host of non-price variables, including fulfillment method (Fulfillment by Amazon is heavily favored), shipping speed, seller rating, and inventory levels. A seller with a higher price but superior fulfillment and ratings will often win the Buy Box over a cheaper rival. This demonstrates a market where the key competition is for algorithmic approval to gain visibility, justifying our focus on platform curation.

Another example is Booking.com's Hotel Rankings. When a user searches for a hotel, the platform presents a ranked list that is not sorted by price by default. A hotel's position in this ranking is a critical determinant of its sales and is influenced by a complex algorithm. Key factors include the commission rate the hotel pays Booking.com, its historical conversion rate on the platform, guest review scores, and participation in programs like "Preferred Partner." A hotel's strategic priority is often to improve its algorithmic ranking to appear on the first page, even if it means paying higher fees or offering amenities, rather than simply being the cheapest option. This again highlights an environment where the battle for platform-curated visibility is the central competitive dynamic. In both examples, the platform acts as a powerful gatekeeper, shaping competition through its control of visibility. Our framework is therefore well-suited to analyzing the strategic implications of this curation power, a central feature of the modern digital economy.

3.2 Platform profit maximization

We now analyze the platform's optimal strategy when self-preferencing is an available, but not mandatory, choice. The game proceeds sequentially: the platform sets a commission rate γ, third-party sellers enter, and finally, the platform chooses how many entrants to display. Backward induction simplifies this to the platform choosing γ and the number of displayed sellers s to maximize profit, subject to the entry constraint. The platform's optimization problem is therefore:

$$\max_{s \in [0,\bar{s}], \gamma \in [0,1]} \Pi_{sp}(s,\gamma) \quad \text{s.t. } s \leq s_0(\gamma)$$

where $\Pi_{sp}(s,\gamma) \equiv \mu^s \left(\frac{b}{h+s}\right)[h\pi_m + s\pi_{sm}(\gamma)]$. The solution is characterized in the following proposition.

Proposition 2 (Optimal Self-Preferencing Strategy) *The platform's decision to self-preference depends on the level of entry at its ideal commission rate, $\hat{\gamma}$. There are two cases:*

1. ***Excessive Entry* ($s_0(\hat{\gamma}) > \hat{s}(\hat{\gamma})$)*:*** *It is strictly optimal for the platform to self-preference. The platform achieves its unconstrained maximum profit by setting $\gamma_{sp} = \hat{\gamma}$ and displaying $s_{sp} = \hat{s}(\hat{\gamma})$.*

2. ***Insufficient Entry* ($s_0(\hat{\gamma}) < \hat{s}(\hat{\gamma})$)*:*** *It is optimal for the platform to* ***not*** *actively self-preference. The outcome is identical to the no-self-preferencing benchmark.*

This proposition highlights that self-preferencing is a tool the platform uses only when facing an excess of third-party sellers. In the *excessive entry* case, self-preferencing becomes a powerful tool. It allows the platform to solve two problems with two instruments. It sets the commission rate $\gamma = \hat{\gamma}$ to solve the first problem—maximizing its revenue from each third-party sale. It then uses self-preferencing to solve the second problem—reducing the number of displayed sellers from the excessive entry level $s_0(\hat{\gamma})$ down to its ideal level, $\hat{s}(\hat{\gamma})$. By separating these two objectives, the platform achieves its unconstrained profit.

In the *insufficient entry* case, the number of sellers entering at the platform's ideal fee, $\hat{\gamma}$, is already below the desired level. The platform's primary problem is attracting more sellers, not fewer. Using self-preferencing to further reduce the number of displayed sellers would be counterproductive. The platform, therefore, forgoes this option, and thus the outcome is identical to the no-self-preferencing benchmark.

To appreciate how valuable this is, consider the alternative. Without this tool, the platform must use the blunt instrument of a high commission fee ($\gamma_{nsp} > \hat{\gamma}$) to deter entry. This can even lead to a surprising "over-deterrence" effect, where the high fee so severely discourages entry that the final number of sellers is even *lower* than what the platform would have displayed with self-preferencing ($s_{nsp} < s_{sp}$). Self-preferencing allows the platform to avoid this inefficient outcome.[3]

First-party capacity and self-preferencing. According to Proposition 2, self-preferencing is triggered by excessive seller entry. The following proposition demonstrates that this excessive entry is a direct consequence of the platform's first-party capacity becoming too large.

Proposition 3 *The entry gap, $s_0(\hat{\gamma}) - \hat{s}(\hat{\gamma})$, which triggers self-preferencing when it is positive, increases with the mass of first-party sellers h, provided that both $s_0(\hat{\gamma})$ and $\hat{s}(\hat{\gamma})$ are positive. Consequently, there exists a threshold for the platform's own retail presence, $\tilde{h}$, such that for any $h > \tilde{h}$, self-preferencing is a strictly profit-maximizing strategy.*

The intuition stems from a "race" between the number of sellers the market supplies (s_0) and the number the platform desires ($\hat{s}$). As the platform's first-party size (h) increases, it becomes more protective of its own sales. While more competition from h naturally reduces the number of third-party entrants (s_0), the platform's ideal number of third-party sellers ($\hat{s}$) shrinks even faster because the negative *weighting effect* becomes more severe. This widening gap means that as a platform's own sales grow, it transitions from a neutral facilitator into a direct competitor with its own sellers, creating a fundamental conflict of interest. In practice, proving that a platform is engaging in algorithmic self-preferencing can be a significant challenge for regulators. This challenge underscores the value of our finding: the platform's first-party market share thus becomes a simple yet powerful heuristic for monitoring anticompetitive risk, as self-preferencing evolves from a mere possibility into a predictable strategic imperative once h is sufficiently large.

In a similar vein, self-preferencing becomes more likely when the mass of buyers is small or when seller entry costs are low.

Corollary 1 *The entry gap, $s_0(\hat{\gamma}) - \hat{s}(\hat{\gamma})$, which triggers self-preferencing, decreases with the the mass of buyers, b, and seller entry cost, k, provided that both $s_0(\hat{\gamma})$ and $\hat{s}(\hat{\gamma})$ are positive. Consequently, self-preferencing is a strictly profit-maximizing strategy when b and k are sufficiently small.*

The intuition is as follows. An increase in the number of buyers b makes the market more attractive, causing a flood of third-party entrants (s_0 increases). While the platform also wants more sellers to serve the larger market ($\hat{s}$ also increases), its enthusiasm is further enhanced because

[3] Lemma 4 in Section 4 establishes the precise conditions that give rise to this inefficient over-deterrence.

a larger third-party seller base mitigates the negative weighting effect. Since the platform's demand for sellers increases more rapidly than the market's supply of sellers, the entry gap shrinks.

A higher entry cost k acts as a natural barrier to entry, reducing the number of third-party sellers, s_0. The platform's ideal number of sellers, $\hat{s}$, is unaffected by this external cost. A higher entry cost, therefore, shrinks the gap by solving the excessive entry problem on the platform's behalf, making self-preferencing a less necessary strategy.

4 Welfare Analysis

The platform's pursuit of profits is not necessarily aligned with the interests of society. To pinpoint the sources of inefficiency, we construct the social optimal allocation that a benevolent planner would choose. This optimum provides the necessary framework for our central policy analysis—evaluating the welfare consequences of a ban on self-preferencing. We conduct this evaluation using two key metrics: total social welfare and consumer surplus.

4.1 Social Welfare Optimality and Distortions

Consider a social planner who can set the commission fee γ and select the number of displayed third-party sellers s (subject to the seller's free-entry condition) to maximize total welfare. A first-party match generates a total surplus $w_m \equiv \pi_m + cs_m$, where cs_m is the consumer surplus at the first-party price p_m. A third-party match generates a total surplus $w_s(\gamma) \equiv \pi_{ss}(\gamma) + \pi_{sm}(\gamma) + cs_s(\gamma)$, where $cs_s(\gamma)$ is the consumer surplus at third-party price $p_s(\gamma)$. The planner's objective is to maximize the social welfare:

$$W(\gamma, s) = \mu^s \left(\frac{b}{h+s}\right) \left\{hw_m + s\Big(\pi_{ss}(\gamma) + \pi_{sm}(\gamma) + cs_s(\gamma)\Big)\right\} - s_E k,$$

which is the total trade surplus minus the entry costs of sellers $s_E k$ with s_E the measure of sellers that enter the platform.

The free-entry condition dictates that third-party sellers enter the market until their expected profit is exactly offset by their entry costs. This drives the net surplus of third-party sellers to zero. The objective then reduces to the combined surplus of consumers and the platform (i.e., first-party sales and commission revenue):

$$\max_{\gamma, s} \quad \mu^s \left(\frac{b}{h+s}\right) \left\{hw_m + s\Big(\pi_{sm}(\gamma) + cs_s(\gamma)\Big)\right\} \quad \text{s.t.} \quad s \leq s_0(\gamma).$$

The planner's problem can be broken down into two parts: setting the optimal commission and choosing the optimal number of sellers. First, consider the commission. The socially optimal commission, denoted γ_w, must be smaller than the platform's private optimum, $\hat{\gamma}$. This is because the social planner maximizes the joint surplus $\pi_{sm}(\gamma) + cs_s(\gamma)$, whereas the platform maximizes only its own profit $\pi_{sm}(\gamma)$. The platform's choice, $\hat{\gamma}$, ignores the negative impact of a higher commission on consumer surplus (as fees are passed through as higher prices). The planner internalizes this negative externality imposed on consumers. Moreover, a lower fee also beneficially relaxes the entry constraint ($s \leq s_0(\gamma)$), expanding the planner's ability to optimize the number of sellers.

With the commission optimally set at γ_w, the planner's problem reduces to choosing the number of displayed third-party sellers. This choice involves a trade-off analogous to the one the platform faces. Increasing s generates a positive matching effect by increasing the total trade volume. However, it also creates a negative weighting effect since the surplus from a first-party sale is greater than the joint surplus from a third-party sale (i.e., $w_m > \pi_{sm}(\gamma_w) + cs_s(\gamma_w)$). The social planner's optimal number of sellers should balance these two effects.

In conclusion, there are two sources of distortions. The *fee distortion*: the platform sets a higher commission fee which exacerbates the double marginalization problem and leads to inefficiently high consumer prices. A social planner, by contrast, would mitigate this by setting $\gamma = \gamma_w$. The *self-preferencing distortion*: the platform curates its marketplace to maximize profits, neglecting consumer surplus.

Despite these distortions, it is worth emphasizing that both the planner and the platform actively manage the number of sellers; neither allows unrestricted entry. In particular, the self-preferencing distortion arises because the platform's curation decision is weighted by its own profits, whereas the planner's is weighted by total trade surplus. Consequently, the platform may feature either too many or too few third-party sellers compared to the social optimum.

In the following, we delve into the sign of self-preferencing distortions by holding the commission fee γ constant. This analysis mirrors a plausible regulatory scenario where authorities might cap fees without directly intervening in marketplace design. The platform's profit-maximizing choice of sellers, $\hat{s}(\gamma)$, is driven by the ratio of its own revenue streams: $\frac{\pi_{sm}(\gamma)}{\pi_m}$, which is the commission revenue from a third-party sale relative to the profit from a first-party sale. In contrast, the planner's choice, $\hat{s}_w(\gamma)$, is driven by the ratio of total social surplus generated by each type of sale: $\frac{cs_s(\gamma)+\pi_{sm}(\gamma)}{w_m}$. The following lemma formalizes this distortion.

Lemma 3 *The platform lists too few third-party sellers, $\hat{s}(\gamma) < \hat{s}_w(\gamma)$, if and only if:*

$$\frac{\pi_{sm}(\gamma)}{cs_s(\gamma)} < \frac{\pi_m}{cs_m}.$$

The lemma shows that the platform lists too few third-party sellers whenever its revenue-to-consumer-surplus ratio for third-party sales is less than the same ratio for its first-party sales. This is a classic case where the profit motive leads to an under-provision of goods that generate high social value. Conversely, when third-party sellers generate high commission revenue for the platform but offer little surplus to consumers, the platform has an incentive to list too many of them.

4.2 Banning Self-Preferencing

We now evaluate the welfare implications of a regulatory ban on self-preferencing. Such a policy requires the platform to display all sellers who enter the market. The impact of this ban depends critically on the platform's equilibrium strategy. Since a ban only has an effect when the market is characterized by *excessive entry* ($s_0(\hat{\gamma}) > \hat{s}(\hat{\gamma})$), our subsequent analysis focuses on this scenario.

When self-preferencing is allowed, the platform sets the optimal commission rate $\hat{\gamma}$, and actively curates the marketplace by displaying a smaller mass of third-party sellers $\hat{s}(\hat{\gamma})$. The resulting social welfare is:

$$W_{sp} \equiv W(\hat{\gamma}, \hat{s}(\hat{\gamma})) = \mu^s \left(\frac{b}{h + \hat{s}(\hat{\gamma})} \right) \{hw_m + \hat{s}(\hat{\gamma})[\pi_{sm}(\hat{\gamma}) + cs_s(\hat{\gamma})]\}.$$

If self-preferencing is banned, the platform loses its ability to curate and must display all entering sellers. Its only strategic tool is the commission rate, which it sets at γ_{nsp}. Social welfare is then:

$$W_{nsp} \equiv W(\gamma_{nsp},\, s_0(\gamma_{nsp})) = \mu^s \left(\frac{b}{h + s_0(\gamma_{nsp})} \right) \{hw_m + s_0(\gamma_{nsp})[\pi_{sm}(\gamma_{nsp}) + cs_s(\gamma_{nsp})]\}.$$

To understand the welfare trade-offs, we can decompose the total welfare difference into two distinct components:

$$W_{sp} - W_{nsp} = \underbrace{W(\hat{\gamma},\, \hat{s}(\hat{\gamma})) - W(\hat{\gamma},\, s_0(\gamma_{nsp}))}_{\text{quantitative effect}} + \underbrace{W(\hat{\gamma},\, s_0(\gamma_{nsp})) - W(\gamma_{nsp},\, s_0(\gamma_{nsp}))}_{\text{pricing effect}}.$$

There are two observations. First, the *pricing effect* is always positive. A ban on self-preferencing incentivizes the platform to raise its commission rate to control entry (i.e., $\gamma_{nsp} > \hat{\gamma}$), which harms both consumer surplus and the platform's commission revenue, thereby reducing social welfare.

The second observation is that the *quantitative effect* is ambiguous. It captures the welfare change from moving the number of displayed sellers from the platform's curated level, $\hat{s}(\hat{\gamma})$, to the level under the ban, $s_0(\gamma_{nsp})$. This change can move the number of sellers either closer to or further from the social optimum, $s_w(\gamma)$. Assuming the welfare function $W(\hat{\gamma}, s)$ is single-peaked in s, the quantitative effect is positive if curation $\hat{s}(\hat{\gamma})$ brings the seller count closer to the social optimum than the uncurated outcome $s_0(\gamma_{nsp})$ would.

The relationship between the curated number of sellers, $\hat{s}(\hat{\gamma})$, and the uncurated number, $s_0(\gamma_{nsp})$, is crucially determined by the platform's first-party capacity, h. We define two thresholds: $\tilde{h}$, below which the platform never self-preferences, and $\bar{h}$, above which the platform operates as a pure first-party monopolist by deterring all third-party entry. The following lemma describes the relationship for intermediate values of $h \in (\tilde{h}, \overline{h})$.

Lemma 4 *There exist h_0 and h_1, satisfying $\tilde{h} < h_0 \leq h_1 < \overline{h}$, such that $\hat{s}(\hat{\gamma}) \leq s_0(\gamma_{nsp})$ when $h \leq h_0$, and $\hat{s}(\hat{\gamma}) \geq s_0(\gamma_{nsp})$ when $h \geq h_1$.*

The lemma reveals a non-monotonic relationship. When the platform's first-party presence is relatively small ($h \leq h_0$), a ban on self-preferencing leads to more third-party sellers being displayed, which is the intuitive outcome. However, when the platform's first-party presence is large ($h \geq h_1$), it responds to a ban on self-preferencing by aggressively raising its commission fee to defend its first-party sales. This "over-deterrence" can be so strong that the number of sellers under a ban on self-preferencing is actually *lower* than what the platform would have curated: $s_0(\gamma_{nsp}) \leq \hat{s}(\hat{\gamma})$.

This interplay leads to our main result on the welfare effects of self-preferencing.

Proposition 4 *Self-preferencing yields higher social welfare ($W_{sp} > W_{nsp}$) under two distinct sets of conditions: (1) $\frac{\pi_{sm}(\hat{\gamma})}{cs_s(\hat{\gamma})} > \frac{\pi_m}{cs_m}$ and $h \in (\tilde{h}, h_0)$; (2) $\frac{\pi_{sm}(\hat{\gamma})}{cs_s(\hat{\gamma})} < \frac{\pi_m}{cs_m}$ and $h \in (h_1, \bar{h})$. If $h \leq \tilde{h}$ or $h \geq \overline{h}$, a ban has no effect, and $W_{sp} = W_{nsp}$.*

The proposition outlines sufficient conditions under which banning self-preferencing can harm welfare. It examines how the welfare outcome is influenced by the interaction of two factors: the type of self-preferencing distortion and the platform's first-party capacity.

In the first case, the platform is prone to listing too many sellers ($\hat{s}(\hat{\gamma}) > s_w(\hat{\gamma})$). When its first-party capacity is small ($h \in (\tilde{h}, h_0)$), a ban exacerbates this problem by forcing even more sellers onto the platform ($s_0(\gamma_{nsp}) \geq \hat{s}(\hat{\gamma})$), moving the outcome further from the social optimum. This creates a positive quantitative effect, which, combined with the positive pricing effect, makes self-preferencing welfare-superior.

In the second case, the platform is prone to listing too few sellers ($\hat{s}(\hat{\gamma}) < s_w(\hat{\gamma})$). When its first-party capacity is large ($h \in (h_1, \bar{h})$), a ban triggers the over-deterrence response, resulting in even fewer sellers ($s_0(\gamma_{nsp}) \leq \hat{s}(\hat{\gamma})$). Once again, the ban pushes the market further from the social optimum, yielding a positive quantitative effect that reinforces the positive pricing effect.

Finally, at the boundaries, a ban is ineffective. For a very small first-party presence ($h \leq \tilde{h}$), the platform does not self-preference. For a very large first-party presence ($h \geq \bar{h}$), it acts as a monopolist regardless of the policy. In both scenarios, the equilibrium outcome is identical, and thus $W_{sp} = W_{nsp}$.

4.2.1 Evaluating a ban from the consumer welfare perspective

We can extend our analysis to evaluate the impact of a self-preferencing ban from the perspective of consumer welfare. Consumer surplus can also be expressed as a function of the commission rate, γ, and the mass of displayed third-party sellers, s:

$$CS(\gamma, s) = \mu^s \left(\frac{b}{h+s}\right) (h \cdot cs_m + s \cdot cs_s(\gamma)) \, .$$

From this, and assuming $CS(\cdot)$ is single-peaked in s, we can define the consumer-optimal number of third-party sellers, $\hat{s}_c(\gamma)$, as the quantity that maximizes this function for a given commission rate:

$$\hat{s}_c(\gamma) = \arg\max_s CS(\gamma, s).$$

The first-order condition of this maximization problem reveals that $\hat{s}_c(\gamma)$ is determined by the ratio of consumer surplus from a third-party match to that from a first-party match, $\frac{cs_s(\gamma)}{cs_m}$. This ratio governs the "weighting effect" from a purely consumer-centric viewpoint. The following lemma compares the platform's profit-maximizing choice of sellers to the consumer-optimal choice, which parallels Lemma 3.

Lemma 5 *The platform displays too few third-party sellers from a consumer surplus perspective,* $\hat{s}(\gamma) < \hat{s}_c(\gamma)$, *if and only if:* $\frac{\pi_{sm}(\gamma)}{cs_s(\gamma)} < \frac{\pi_m}{cs_m}$.

We now state the main result for consumer surplus, denoting CS_{sp} as the consumer surplus with self-preferencing and CS_{nsp} as the surplus without it.

Proposition 5 *Self-preferencing yields higher consumer surplus* ($CS_{sp} > CS_{nsp}$) *under two distinct sets* *of conditions: (1)* $\frac{\pi_{sm}(\hat{\gamma})}{cs_s(\hat{\gamma})} > \frac{\pi_m}{cs_m}$ *and* $h \in (\tilde{h}, h_0)$*; (2)* $\frac{\pi_{sm}(\hat{\gamma})}{cs_s(\hat{\gamma})} < \frac{\pi_m}{cs_m}$ *and* $h \in (h_1, \bar{h})$*. If* $h \leq \tilde{h}$ *or* $h \geq \bar{h}$*, a ban has no effect, and* $CS_{sp} = CS_{nsp}$*.*

The reasoning behind this proposition mirrors the analysis of social welfare, hinging on the combined impact of a pricing effect and a quantitative effect on consumers. First, a positive pricing effect exists because a ban induces the platform to set a higher commission fee, which harms consumers. Second, a positive quantitative effect also exists because under the two sets of conditions, a ban consistently pushes the number of displayed sellers further away from the consumer-optimal level.

5 Participation Fee as a Substitute for Self-Preferencing

In our baseline model, the platform uses self-preferencing to remedy excessive seller entry. This raises a natural question: could a participation fee serve as a substitute for self-preferencing? In this section, we explore this possibility and compare the platform's optimal strategy when using these two instruments.

For any given commission rate γ,[4]suppose the platform wishes to have a target number of third-party sellers, s'_D, where $s'_D < s_0(\gamma)$. The platform can achieve this in two ways. Using *self-preferencing*, more sellers (s'_E) enter than are displayed (s'_D), with the entry condition being

$$\mu^s\left(\frac{b}{h+s'_D}\right)\pi_{ss}(\gamma)\frac{s'_D}{s'_E} = k.$$

Alternatively, the platform can charge a non-negative *participation fee*), $F \geq 0$. This fee effectively raises the entry cost, reducing the number of entrants to the target level, s'_D, without needing to curate. The entry condition becomes

$$\mu^s\left(\frac{b}{h+s'_D}\right)\pi_{ss}(\gamma) = k + F.$$

By setting $F = k\left(\frac{s'_E}{s'_D} - 1\right)$, the platform can achieve the exact same number of displayed sellers. This shows that for reaching a specific seller count, fees and self-preferencing are perfect substitutes. However, as the following lemma states, they are not strategically equivalent.

[4]The platform's profit is $\Pi = \mu^s\left(\frac{b}{h+s'_D}\right)\left[h\pi_m + s'_D(\pi_{sm}(\gamma) + \pi_{ss}(\gamma))\right] - s'_E k$. For any target outcome—a pair of entered and displayed sellers, (s'_E, s'_D)—that can be implemented with a commission rate $\gamma > 0$, the same outcome can also be implemented with $\gamma = 0$. This is because setting $\gamma = 0$ maximizes the potential pool of entrants ($s_0(0) > s_0(\gamma)$). Since setting $\gamma = 0$ is always feasible and yields a higher profit for any given quantity of sellers (as $\max_\gamma(\pi_{sm}(\gamma) + \pi_{ss}(\gamma)) = \pi_{sm}(0) + \pi_{ss}(0)$), the optimal commission rate must be $\gamma = 0$.

Lemma 6 *When the platform can use both self-preferencing and a participation fee, its profit-maximizing strategy is to use the participation fee and not engage in self-preferencing.*

The intuition behind this result lies in efficiency. Self-preferencing is inherently wasteful because more sellers enter the market (s'_E) than are ultimately displayed (s'_D). These undisplayed sellers incur the entry cost k but do not contribute to the matching process. A participation fee, by contrast, is a direct transfer. It allows the platform to ensure that only the desired number of sellers find it profitable to enter, and all who pay the cost are subsequently displayed. Given that the fee is a more efficient instrument for controlling entry, the platform will always prefer it when both tools are available.

Furthermore, if the platform were to use a participation fee to replicate the seller quantity from the self-preferencing outcome, $\hat{s}(\hat{\gamma})$, the resulting social welfare would be

$$\begin{aligned} W_F &= \mu^s \left(\frac{b}{h + \hat{s}(\hat{\gamma})} \right) \{hw_m + \hat{s}(\hat{\gamma})[\pi_{sm}(\hat{\gamma}) + \pi_{ss}(\hat{\gamma}) + cs_s(\hat{\gamma})]\} - \hat{s}(\hat{\gamma})k \\ &= \underbrace{\mu^s \left(\frac{b}{h + \hat{s}(\hat{\gamma})} \right) \{hw_m + \hat{s}(\hat{\gamma})[\pi_{sm}(\hat{\gamma}) + cs_s(\hat{\gamma})]\}}_{=W_{sp}} + \hat{s}(\hat{\gamma})F > W_{sp}. \end{aligned}$$

Therefore, the participation fee is a superior instrument to self-preferencing from a social welfare perspective. By directly pricing market access, it ensures all sellers who pay to enter are displayed, obviating the need for the wasteful curation inherent in self-preferencing. The superior efficiency of participation fees points toward a more nuanced policy direction. A constructive regulatory approach could therefore shift its focus from banning specific practices to promoting transparent mechanisms like participation fees.

5.1 Comparing Participation Fee and Self-Preferencing

Having established that a participation fee is the superior instrument, we now compare the market structures emerging from the two distinct regimes: one reliant on self-preferencing and the other on a participation fee. While a platform with access to a powerful surplus-extraction tool like a participation fee would ideally set its commission to zero, our analysis proceeds for a fixed commission rate. This approach allows us to cleanly isolate how each instrument—a lump sum fee versus curation—incentivizes the platform's choice of seller quantity. Furthermore, this approach is directly relevant to policy contexts, such as a commission floor, where a platform's commission may be constrained to be positive.

First, consider the participation fee regime. When the platform uses a lump sum fee to control entry, it can precisely tune the number of entrants. The fee allows the platform to act as a residual claimant on the total surplus generated by the supply side. By substituting the free-entry condition ($F = \mu^s(\cdot)\pi_{ss}(\gamma) - k$), the platform's problem becomes equivalent to choosing the number of sellers that maximizes the total profits of the platform and third-party sellers:

$$\max_{s\in[0,\bar{s}]} \quad \Pi_F(s;\gamma) = \mu^s\left(\frac{b}{h+s}\right)\Big[h\pi_m + s\big(\pi_{sm}(\gamma) + \pi_{ss}(\gamma)\big)\Big] - sk$$

Assume the objective is single-peaked in s and let $\hat{s}_F(\gamma)$ be the solution to this problem. This is the platform's ideal number of sellers when it uses F, as it perfectly internalizes the sellers' entry cost. $\hat{s}_F(\gamma)$ decreases in γ, as a higher γ exacerbates double marginalization and reduces the total surplus that can be extracted.

Next, we compare this outcome, $\hat{s}_F(\gamma)$, to the optimal number of sellers in the unconstrained optimal number of sellers, $\hat{s}(\gamma)$. Recall that $\hat{s}(\gamma)$ is the number of sellers that maximizes the platform's gross revenue from sales, *ignoring* seller entry costs. In contrast, $\hat{s}_F(\gamma)$ maximizes the platform's net profit by *internalizing* seller entry costs. This difference drives the result in the following proposition.

Proposition 6 *Suppose the platform has a concave objective under both regimes, then $\hat{s}_F(\gamma) \leq \hat{s}(\gamma)$ if and only if*

$$\mu^s\left(\frac{b}{h+\hat{s}(\gamma)}\right)\pi_{ss}(\gamma)\cdot\frac{h\pi_m}{h\pi_m + \hat{s}(\gamma)\pi_{sm}(\gamma)} \leq k. \tag{7}$$

Condition (7) highlights the difference between the two regimes. A platform using a participation fee *internalizes* the full surplus generated by a marginal seller, since it can be extracted via the fee. However, adding sellers also dilutes its profitable first-party sales, creating a crowding-out effect. The condition compares the seller's surplus, adjusted for this first-party composition effect, with the seller's entry cost, k. The direction of this comparison depends critically on market parameters. A higher *entry cost* k, for instance, directly reduces the net surplus the platform can extract, thus lowering its optimal seller count, $\hat{s}_F(\gamma)$, and making it more likely that $\hat{s}_F(\gamma) \leq \hat{s}(\gamma)$. The effect of the platform's *first-party capacity*, h, is more complex. As h increases, the negative crowding-out effect on the platform's own sales becomes more severe. In response, the curation-only platform sharply reduces its target number of sellers, $\hat{s}(\gamma)$. This reduction in total competition makes each remaining seller slot more valuable by increasing the matching probability. A platform using a fee can capture this additional surplus, creating a stronger incentive to attract sellers. Therefore, for larger values of h, we may see $\hat{s}_F(\gamma) > \hat{s}(\gamma)$.

6 Conclusion

This paper demonstrates that platform self-preferencing is not an inherently anti-competitive practice, but rather a response to the excessive entry of third-party sellers. The strategic value of self-preferencing lies in that it allows the platform to decouple its objectives of managing per-transaction revenue and fine-tuning seller quantity. A regulatory ban removes this tool, forcing the platform to rely on the blunt instrument of high commission fees to deter entry. This can trigger an inefficient "over-deterrence" effect, where the number of sellers is pushed even lower than what the platform would have chosen if self-preferencing were allowed. By highlighting the critical role of the platform's first-party capacity and the ambiguous nature of welfare outcomes, our findings caution against one-size-fits-all bans, which can trigger these unintended consequences and ultimately harm consumer and social welfare.

References

ANDERSON, S. P., DE PALMA, A., AND NESTEROV, Y. "Oligopolistic Competition and the Optimal Provision of Products." *Econometrica*, Vol. 63 (1995), 1281–1301.

ANDERSON, S. P., AND DEFOLIE, Ö. B. "Hybrid platform model: monopolistic competition and a dominant firm." *RAND Journal of Economics*, Vol. 55 (2024), 684–718.

CHEN, Y., AND ZHANG, T. "Entry and Welfare in Search Markets." *The Economic Journal*, Vol. 128 (2018), 55–80.

CHI, C.-K., CHOI, J. P., HAHN, J.-H., AND KIM, S. "Platform Incentives and the Limits of Self-Preferencing Regulation." Working paper, 2025.

DE CORNIÈRE, A., AND TAYLOR, G. "A model of biased intermediation." *RAND Journal of Economics*, Vol. 50 (2019), 854–882.

DENDORFER, F. "First-party selling and self-preferencing." *International Journal of Industrial Organization*, Vol. 97 (2024), 103098.

GAUTIER, P., HU, B., AND WATANABE, M. "Marketmaking Middlemen." *The RAND Journal of Economics*, Vol. 54 (2023), 83–103.

HERVAS-DRANE, A., AND SHELEGIA, S. "Retailer-Led Marketplaces." *Management Science* (2025).

MANKIW, N. G., AND WHINSTON, M. D. "Free Entry and Social Inefficiency." *The RAND Journal of Economics*, Vol. 17 (1986), 48–58.

SATO, S., AND KITTAKA, Y. "Search-Order Design by Dual-Role Platforms." Working paper, 2024.

TAN, G., AND ZHOU, J. "The Effects of Competition and Entry in Multi-sided Markets." *The Review of Economic Studies*, Vol. 88 (2021), 1002–1030.

WANG, Z., AND WRIGHT, J. "Ad valorem platform fees, indirect taxes, and efficient price discrimination." *RAND Journal of Economics*, Vol. 48 (2017), 467–484.

ZENNYO, Y. "Platform Encroachment and Own-content Bias." *The Journal of Industrial Economics*, Vol. 70 (2022), 684–710.

Appendix A: Proofs

Proof of Proposition 1

Excessive Entry ($s_0(\hat{\gamma}) > \hat{s}(\hat{\gamma})$): We want to show $\gamma_{nsp} \in (\hat{\gamma}, \gamma_r]$.

From the first-order condition, we know the optimum must satisfy $\gamma_{nsp} > \hat{\gamma}$. Assuming for contradiction that $\gamma_{nsp} > \gamma_r$, it then follows that $s_0(\gamma_{nsp}) < s_0(\gamma_r)$. We can then show that:

$$\Pi(\gamma_{nsp}, s_0(\gamma_{nsp})) < \Pi(\gamma_r, s_0(\gamma_{nsp})) \leq \Pi(\gamma_r, s_0(\gamma_r)).$$

The first inequality holds because the platform's profit function is decreasing in γ in this region. The second inequality holds because, for a fixed commission rate γ_r, the platform's profit is maximized when the number of third-party sellers is equal to $s_0(\gamma_r) = \hat{s}(\gamma_r)$. This again leads to a contradiction. Thus, we must have $\gamma_{nsp} \leq \gamma_r$.

Insufficient Entry ($s_0(\hat{\gamma}) < \hat{s}(\hat{\gamma})$): We want to show $\gamma_{nsp} \in [\gamma_l, \hat{\gamma})$.

From the first-order condition, we know the optimum must satisfy $\gamma_{nsp} < \hat{\gamma}$. Assuming for contradiction that $\gamma_{nsp} < \gamma_l$, it then follows that $s_0(\gamma_{nsp}) > s_0(\gamma_l)$. We can then show that:

$$\Pi(\gamma_{nsp}, s_0(\gamma_{nsp})) < \Pi(\gamma_l, s_0(\gamma_{nsp})) \leq \Pi(\gamma_l, s_0(\gamma_l)).$$

The first inequality holds because the platform's profit function is increasing in γ in this region. The second inequality holds because, for a fixed commission rate γ_l, the platform's profit is maximized when the number of third-party sellers is equal to $s_0(\gamma_l) = \hat{s}(\gamma_l)$. This again leads to a contradiction. Thus, we must have $\gamma_{nsp} \geq \gamma_l$.■

Proof of Lemma 2

For the equilibrium number of sellers in the benchmark model, $s_0(\gamma)$, the following condition holds by definition:

$$\mu^s\left(\frac{b}{h + s_0(\gamma)}\right)\pi_{ss}(\gamma) \cdot s_0(\gamma) = s_0(\gamma) \cdot k.$$

Now, consider a case where the number of displayed sellers is less than this equilibrium value, $s_D < s_0(\gamma)$. We have the following inequality:

$$\mu^s\left(\frac{b}{h + s_D}\right)\pi_{ss}(\gamma) \cdot s_D > s_D \cdot k.$$

From the monotonicity of the function $\mu^s\left(\frac{b}{h+s}\right) \cdot s$, we know that for $s_D < s_0(\gamma)$, the following inequality holds:

$$\mu^s\left(\frac{b}{h + s_D}\right) \cdot s_D < \mu^s\left(\frac{b}{h + s_0(\gamma)}\right) \cdot s_0(\gamma).$$

Furthermore, given that the function $s \cdot k$ is monotonically increasing, the inequalities above imply (by the Intermediate Value Theorem) that there must exist some value $s_E \in (s_D, s_0(\gamma))$ that satisfies the free-entry condition for a given s_D.

Equality is only achieved at the boundary: we will have $s_D = s_E = s_0(\gamma)$ if and only if s_D is set to $s_0(\gamma)$.

■

Proof of Proposition 2

Excessive Entry ($s_0(\hat{\gamma}) > \hat{s}(\hat{\gamma})$): When the platform is allowed to engage in self-preferencing, the feasible set of s given any γ is $s \in [0, s_0(\gamma)]$. Since the premise of this case is that $s_0(\hat{\gamma}) > \hat{s}(\hat{\gamma})$, the unconstrained ideal number of sellers, $\hat{s}(\hat{\gamma})$, is a feasible when the platform sets $\gamma = \hat{\gamma}$. Therefore, the platform can attain the unconstrained optimal solution $(\gamma_{sp},\ s_{sp}) = (\hat{\gamma},\ \hat{s}(\hat{\gamma}))$.

Insufficient Entry ($s_0(\hat{\gamma}) < \hat{s}(\hat{\gamma})$): In this case, we show that the outcome with self-preferencing is identical to the no-self-preferencing benchmark. Suppose the platform's optimal choice is (γ_{sp}, s_{sp}), where $s_{sp} \in [0, s_0(\gamma_{sp})]$. We first establish that the optimal choice must occur in a region where $s_0(\gamma_{sp}) \leq \hat{s}(\gamma_{sp})$. Assume for contradiction that $s_0(\gamma_{sp}) > \hat{s}(\gamma_{sp})$. Then by the same argument as in Corollary 1, there exists $\gamma_l \in (\gamma_{sp}, \hat{\gamma})$ (or $\gamma_r \in (\hat{\gamma}, \gamma_{sp})$) such that the following holds:

$$\Pi(\gamma_l, \hat{s}(\gamma_l)) > \Pi(\gamma_l, \hat{s}(\gamma_{sp})) \geq \Pi(\gamma_{sp}, \hat{s}(\gamma_{sp})),$$

or

$$\Pi(\gamma_r, \hat{s}(\gamma_r)) > \Pi(\gamma_r, \hat{s}(\gamma_{sp})) \geq \Pi(\gamma_{sp}, \hat{s}(\gamma_{sp})).$$

This contradicts that (γ_{sp}, s_{sp}) is optimal. Therefore, any optimal choice must satisfy $s_0(\gamma_{sp}) \leq \hat{s}(\gamma_{sp})$.

Given this condition, it follows that:

$$\Pi(\gamma_{sp}, s_{sp}) \leq \Pi(\gamma_{sp}, s_0(\gamma_{sp})) \leq \Pi(\gamma_{nsp}, s_0(\gamma_{nsp})).$$

The first inequality holds because profit is increasing in s in this region, so the platform chooses the maximum feasible amount, $s_{sp} = s_0(\gamma_{sp})$. The second inequality holds by definition of $(\gamma_{nsp}, s_0(\gamma_{nsp}))$ being the optimal choice in this regime.

This shows that the platform cannot achieve a strictly higher profit with self-preferencing. Its optimal choice must therefore coincide with the no-self-preferencing outcome; that is, $\gamma_{sp} = \gamma_{nsp}$ and $s_{sp} = s_0(\gamma_{nsp})$. The outcome is identical to the no-self-preferencing benchmark. ■

Proof of Proposition 3

We first establish the derivatives of the two key functions with respect to h. Seller entry changes as follows:

$$\frac{\partial s_0(\hat{\gamma})}{\partial h} = -1.$$

In contrast, the derivative of the unconstrained ideal number of sellers is

$$\frac{\partial \hat{s}(\hat{\gamma})}{\partial h} = -\frac{\frac{\partial \text{F.O.C}}{\partial h}}{\frac{\partial \text{F.O.C}}{\partial s}} = -\frac{\frac{\partial \text{F.O.C}}{\partial s} - \mu^{s'}\left(\frac{b}{h+s}\right)[\pi_m - \pi_{sm}(\gamma)]\frac{b}{(h+s)^2}}{\frac{\partial \text{F.O.C}}{\partial s}} < -1.$$

Taken together, these results show that the gap, $s_0(\hat{\gamma}) - \hat{s}(\hat{\gamma})$, is increasing in h, provided that both $s_0(\hat{\gamma})$ and $\hat{s}(\hat{\gamma})$ are positive.

It is straightforward to show that $\frac{\partial s_0(\hat{\gamma})}{\partial k} < 0$ and that $s_0(\gamma)$ is always positive when $k = 0$. To ensure that a region exists where it is strictly optimal for the platform to self-preference, the entry cost, k, must not be prohibitively high. We formalize this by defining a critical threshold for the entry cost, $\tilde{k}$, as the value that satisfies the following condition:

$$\frac{\partial[\mu^s\left(\frac{b}{s+h}\right)s]}{\partial s}\pi_{sm}(\hat{\gamma}) + \frac{\partial \mu^s\left(\frac{b}{s+h}\right)}{\partial s}h\pi_m\bigg|_{h=\frac{b}{\mu^{s^{-1}}\left(\frac{\tilde{k}}{\pi_{ss}(\hat{\gamma})}\right)}, s=0} = 0.$$

We assume $k < \tilde{k}$, which ensures that there exists a unique threshold $\tilde{h} \in (0, +\infty)$ where the following equality holds:

$$s_0(\hat{\gamma})\big|_{h=\tilde{h}} = \hat{s}(\hat{\gamma})\big|_{h=\tilde{h}} > 0.$$

It follows that for $h \le \tilde{h}$, we have $s_0(\hat{\gamma}) \le \hat{s}(\hat{\gamma})$, and for $h > \tilde{h}$, we have $s_0(\hat{\gamma}) > \hat{s}(\hat{\gamma})$.

Note on a Corner Case: If the entry cost k is very large (i.e., $k \ge \tilde{k}$), the gap $s_0(\hat{\gamma}) - \hat{s}(\hat{\gamma})$ remains negative for all $h < \tilde{h}$ and only becomes zero at the threshold, as shown below:

$$s_0(\hat{\gamma})\big|_{h=\tilde{h}} = \hat{s}(\hat{\gamma})\big|_{h=\tilde{h}} = 0.$$

In this case, the platform will never use self-preferencing because the market is always undersupplied with sellers. We assume that k is small enough to exclude this limiting case from our main analysis. ■

Proof of Lemma 4

Since $s_0(\gamma)$ is strictly decreasing in γ, the platform's optimal choice of commission rate γ effectively corresponds to choosing an optimal third-party seller scale s. The associated commission is then given by $\gamma_0^{-1}(s)$. Thus, in both the self-preferencing and non-self-preferencing regimes, the platform selects the value of s that maximizes its profit.

When there is no self-preferencing, the first-order condition (F.O.C.) for the platform's profit with respect to s is

$$\frac{\partial[\mu^s\left(\frac{b}{s+h}\right)s]}{\partial s}\pi_{sm}(\gamma_0^{-1}(s)) + \frac{\partial\mu^s\left(\frac{b}{s+h}\right)}{\partial s}h\pi_m + \frac{\partial\pi_{sm}(\gamma_0^{-1}(s))}{\partial s}\mu^s\left(\frac{b}{s+h}\right)s = 0.$$

When there is self-preferencing, the F.O.C. for the platform's profit with respect to s is

$$\frac{\partial[\mu^s\left(\frac{b}{s+h}\right)s]}{\partial s}\pi_{sm}(\hat{\gamma}) + \frac{\partial\mu^s(\frac{b}{s+h})}{\partial s}h\pi_m = 0.$$

First, we prove the existence of $\overline{h}$:

Since $\frac{\partial\hat{s}(\hat{\gamma})}{\partial h} < 0$, we can define a threshold, $\overline{h}$, as follows:

$$\frac{\partial[\mu^s\left(\frac{b}{s+h}\right)s]}{\partial s}\pi_{sm}(\hat{\gamma}) + \frac{\partial\mu^s\left(\frac{b}{s+h}\right)}{\partial s}h\pi_m\bigg|_{h=\overline{h},s=0} = 0.$$

Therefore, when $h \ge \overline{h}$, we have $\hat{s}(\hat{\gamma}) = 0$.

The first-order condition for the no-self-preferencing case, evaluated at $h = \overline{h}$ and $s = 0$, is given by:

$$\begin{aligned}
&\frac{\partial[\mu^s\left(\frac{b}{s+h}\right)s]}{\partial s}\pi_{sm}(\gamma_0^{-1}(s)) + \frac{\partial\mu^s\left(\frac{b}{s+h}\right)}{\partial s}h\pi_m + \frac{\partial\pi_{sm}(\gamma_0^{-1}(s))}{\partial s}\mu^s\left(\frac{b}{s+h}\right)s\bigg|_{h=\overline{h},s=0} \\
&= \frac{\partial[\mu^s\left(\frac{b}{s+h}\right)s]}{\partial s}\pi_{sm}(\gamma_0^{-1}(s)) + \frac{\partial\mu^s\left(\frac{b}{s+h}\right)}{\partial s}h\pi_m\bigg|_{h=\overline{h},s=0} \\
&< \frac{\partial[\mu^s\left(\frac{b}{s+h}\right)s]}{\partial s}\pi_{sm}(\hat{\gamma}) + \frac{\partial\mu^s\left(\frac{b}{s+h}\right)}{\partial s}h\pi_m\bigg|_{h=\overline{h},s=0} \le 0.
\end{aligned}$$

Therefore, when $h \ge \overline{h}$, we also have $s_0(\gamma_{nsp}) = 0$.

Second, we prove the existence of h_1:

There exists a threshold $\overline{h}_{nsp}$ such that at $h = \overline{h}_{nsp}$ and $s = 0$, the first-order condition for the no-self-preferencing case is

$$\frac{\partial[\mu^s\left(\frac{b}{s+h}\right)s]}{\partial s}\pi_{sm}(\gamma_0^{-1}(s)) + \frac{\partial\mu^s\left(\frac{b}{s+h}\right)}{\partial s}h\pi_m\bigg|_{h=\overline{h}_{nsp},\, s=0} = 0.$$

At this same point ($h = \overline{h}_{nsp}$, $s = 0$), for the self-preferencing case, we have:

$$\frac{\partial[\mu^s\left(\frac{b}{s+h}\right)s]}{\partial s}\pi_{sm}(\hat{\gamma}) + \frac{\partial\mu^s\left(\frac{b}{s+h}\right)}{\partial s}h\pi_m\Big|_{h=\overline{h}_{nsp},\, s=0} > 0.$$

When $h \in [\overline{h}_{nsp}, \overline{h}]$, we have $s_0(\gamma_{nsp}) = 0$. Given the above, it follows that $\hat{s}(\hat{\gamma}) > s_0(\gamma_{nsp}) = 0$ in this range. By continuity, we know that there exists a threshold h_1 ($h_1 \leq \overline{h}_{nsp}$), such that when $h_1 < h < \overline{h}$, we have $\hat{s}(\hat{\gamma}) > s_0(\gamma_{nsp})$.

Third, we prove the existence of h_0:

First, recall the platform's profit under no self-preferencing, which is given by the free entry condition:

$$\Pi_{nsp} = k\frac{h\pi_m + s_0(\gamma_{nsp})\pi_{sm}(\gamma_{nsp})}{\pi_{ss}(\gamma_{nsp})}.$$

The marginal revenue for the platform with respect to h in this regime is

$$MR_{nsp} = \frac{\mathrm{d}\Pi_{nsp}}{\mathrm{d}h} = \frac{\partial\Pi_{nsp}}{\partial h} = k\frac{\pi_m - \pi_{sm}(\gamma_{nsp})}{\pi_{ss}(\gamma_{nsp})} = [\pi_m - \pi_{sm}(\gamma_{nsp})]\mu^s\left(\frac{b}{h + s_0(\gamma_{nsp})}\right).$$

Next, consider the scenario under self-preferencing. When $h > \tilde{h}$, the platform will choose $\gamma = \hat{\gamma}$. The platform's profit in this case is

$$\Pi_{sp} = \mu^s\left(\frac{b}{h + \hat{s}(\hat{\gamma})}\right)(h\pi_m + \hat{s}(\hat{\gamma})\pi_{sm}(\hat{\gamma})).$$

The marginal profit MR_{sp} with respect to h is

$$MR_{sp} = \frac{\mathrm{d}\Pi_{sp}}{\mathrm{d}h} = \frac{\partial\Pi_{sp}}{\partial h} = \underbrace{\frac{\partial\Pi_{sp}}{\partial s}}_{=0} + [\pi_m - \pi_{sm}(\hat{\gamma})]\mu^s\left(\frac{b}{h + \hat{s}(\hat{\gamma})}\right).$$

We assert that there exists a threshold $h_0' > \tilde{h}$, such that for all $h \in [\tilde{h},\, h_0')$, we have $MR_{sp} > MR_{nsp}$.

To prove this by contradiction, suppose such a threshold h_0' does not exist. Then there must exist another $h_0'' > \tilde{h}$, such that for all $h \in [\tilde{h},\, h_0'']$, we would have $MR_{sp} \leq MR_{nsp}$. In this case, it would follow that the platform's profit under self-preferencing, Π_{sp}, is less than the profit under no-self-preferencing, Π_{nsp}, for all $h \in [\tilde{h},\, h_0'']$. This contradicts our earlier result which stated that when $h > \tilde{h}$ (implying $\hat{s}(\hat{\gamma}) < s_0(\hat{\gamma})$), we have $\Pi_{sp} > \Pi_{nsp}$. Therefore, such a threshold h_0' must exist.

Since $MR_{sp} > MR_{nsp}$ for $h \in [\tilde{h},\, h_0')$, and we also have $[\pi_m - \pi_{sm}(\hat{\gamma})] < [\pi_m - \pi_{sm}(\gamma_{nsp})]$, this implies that $\hat{s}(\hat{\gamma}) < s_0(\gamma_{nsp})$ within this interval.

By continuity, we know that there exists a threshold h_0 ($h_0 \geq h_0'$), such that when $\tilde{h} < h < h_0$, we have $\hat{s}(\hat{\gamma}) < s_0(\gamma_{nsp})$. ■

Proof of Lemma 6

Let s be the platform's target number of displayed third-party sellers. Suppose the platform uses a combination of a participation fee, F', and self-preferencing to achieve this. Let s' be the total mass of third-party sellers who choose to enter, where by definition $s' \geq s$. The display probability is therefore s/s', with $s/s' \leq 1$.

The entry condition is now:

$$\mu^s\left(\frac{b}{h+s}\right)\pi_{ss}(\gamma)\frac{s}{s'} = k + F'.$$

The platform's profit is the sum of its profit from matching and the revenue from participation fees:

$$\begin{aligned}\Pi &= \mu^s\left(\frac{b}{h+s}\right)[h\pi_m + s\pi_{sm}(\gamma)] + s'F' \\ &= \mu^s\left(\frac{b}{h+s}\right)[h\pi_m + s(\pi_{sm}(\gamma)+\pi_{ss}(\gamma))] - s'k.\end{aligned}$$

From the expression, we can see that the platform's profit, Π, is strictly decreasing in the total mass of third-party sellers who choose to enter, s'. Therefore, to maximize its profit for a given target s, the platform has an incentive to minimize s'. The minimum feasible value for s' is s, which occurs when the display probability $s/s' = 1$.

Thus, the optimal strategy is to set a participation fee, F, that induces exactly s sellers to enter and then displays all of them. This fee is determined by the simplified entry condition where $s' = s$:

$$\mu^s\left(\frac{b}{h+s}\right)\pi_{ss}(\gamma) = k + F.$$

■

Proof of Proposition 6

The first-order condition for the optimal number of sellers, $\hat{s}_F(\gamma)$, is

$$-\mu^{s'}\left(\frac{b}{h+s}\right)\left[h\pi_m + s\big(\pi_{sm}(\gamma)+\pi_{ss}(\gamma)\big)\right]\frac{b}{(h+s)^2} + \big(\pi_{sm}(\gamma)+\pi_{ss}(\gamma)\big)\mu^s\left(\frac{b}{h+s}\right)\Big|_{s=\hat{s}_F(\gamma)} = k.$$

Substitute $\hat{s}(\gamma)$, into the left-hand side (LHS) of the first-order condition for $\hat{s}_F(\gamma)$, which yields:

$$LHS|_{s=\hat{s}(\gamma)} = -\mu^{s'}\left(\frac{b}{h+s}\right)s\pi_{ss}(\gamma)\frac{b}{(h+s)^2} + \pi_{ss}(\gamma)\mu^s\left(\frac{b}{h+s}\right)\Bigg|_{s=\hat{s}(\gamma)}.$$

From the first-order condition for $\hat{s}(\gamma)$, we can further obtain:

$$\begin{aligned}&\mu^{s'}\left(\frac{b}{h+s}\right)s\pi_{ss}(\gamma)\frac{b}{(h+s)^2}\Bigg|_{s=\hat{s}(\gamma)} \\ &= \frac{s\pi_{sm}(\gamma)}{h\pi_m + s\pi_{sm}(\gamma)}\pi_{ss}(\gamma)\mu^s\left(\frac{b}{h+s}\right)\Bigg|_{s=\hat{s}(\gamma)}.\end{aligned}$$

This is equivalent to stating that:

If and only if $\mu^s\left(\frac{b}{h+\hat{s}(\gamma)}\right)\pi_{ss}(\gamma)\cdot\frac{h\pi_m}{h\pi_m+\hat{s}(\gamma)\pi_{sm}(\gamma)} \le k$, then $\hat{s}_F(\gamma) \le \hat{s}(\gamma)$.■

Appendix B: Micro-Foundation of Matching Function

We consider a market with a mass of B buyers and S sellers operating within a product space of N distinct variants. Each buyer has a single "ideal" variant from which they can derive positive utility; all other variants provide zero utility. Buyers' ideal variants are assumed to be independently and uniformly distributed across the N product types.

The matching process unfolds sequentially. First, the S sellers are randomly and independently assigned to one of the N product variants, where it is possible for multiple sellers to be assigned to the same variant. Second, for each buyer, the platform observes their ideal variant and recommends a seller who offers that specific variant. If there are multiple sellers in the variant, the platform randomly picks one and recommends to the buyer. Finally, after being matched, the seller sets a price p, and the buyer draws a utility u from a distribution $D(u)$ and purchases the product if and only if $u \geq p$.

We start with the case where all measures (B, S, N) are finite numbers. First, we establish the probability that a buyer finds at least one seller offering their ideal variant. Since each of the S sellers independently chooses any given variant with probability $1/N$, the probability that no seller offers a specific variant is $(1 - 1/N)^S$. The buyer's matching probability is therefore:

$$P(\text{matched}) = 1 - \left(1 - \frac{1}{N}\right)^S$$

From an individual seller's perspective, a seller who has chosen to offer a particular variant, n, faces two sources of randomness. The number of buyers whose ideal product is variant n follows a **Binomial distribution**, $\text{Binomial}(B, 1/N)$. Similarly, the number of other competing sellers offering the same variant is also a random variable, K, distributed as $\text{Binomial}(S-1, 1/N)$. These two factors determine the expected number of buyers per seller:

$$\mathbb{E}[\text{matches/seller}] = \frac{B}{N} \cdot \mathbb{E}\left[\frac{1}{1+K}\right]$$

where $K \sim \text{Binomial}(S-1, 1/N)$ is the number of competing sellers for the same variant.

We now analyze the model in the large market limit, as $B, S, N \to \infty$ while holding the key ratios constant: the seller density, $\delta = S/N$ and buyer-seller ratio B/S. In this limit, the buyer's matching probability converges to the exponential form:

$$P(\text{matched}) = 1 - e^{-\delta}.$$

The number of competing sellers converges in distribution to a Poisson random variable, $K \sim \text{Poisson}(\delta)$. Using the known result that $\mathbb{E}\left[\frac{1}{1+K}\right] = \frac{1-e^{-\delta}}{\delta}$, the seller's expected number of matches becomes:

$$\begin{aligned}
\mathbb{E}[\text{matches/seller}] &= \frac{B}{S} \cdot \delta \cdot \mathbb{E}\left[\frac{1}{1+K}\right] \\
&= \frac{B}{S} \cdot \delta \cdot \left(\frac{1-e^{-\delta}}{\delta}\right) \\
&= \frac{B}{S}(1 - e^{-\delta})
\end{aligned}$$

We can verify that the aggregate number of matches is consistent from both perspectives. From the buyer side, total matches are $B(1 - e^{-\delta})$. From the seller side, total matches are $S \cdot \frac{B}{S}(1 - e^{-\delta}) = B(1 - e^{-\delta})$. Furthermore, if we consider the special case where the buyer density is one ($B/N = 1$, which implies $\delta = S/B$), the total number of matches becomes $B(1 - e^{-S/B})$. This result is equivalent to standard urn-ball matching function.