One-sided congestion and information asymmetry in a Monopoly Platform

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Declarations of interest none

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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Abstract

The present research tackles an intriguing issue by focusing on the optimal pricing strategy for a two-sided monopoly platform that serves two distinct sides: buyers and sellers. The platform faces asymmetric information regarding the value sellers place on each unit of product with certain quality traded, with sellers categorized into two types: high and low. The platform cannot identify each seller's type, leading to an adverse selection problem. To address this, the platform establishes a pricing strategy for sellers while examining its impact on pricing for buyers. The problem is analyzed in the presence of indirect network externalities. The impact of seller participation on buyers can fluctuate depending on the extent of seller participation and sensitivity of buyers to it. We break down the network externalities reaching buyers into two components: a congestion effect and a positive network benefit effect. We then determine the optimal pricing for the monopoly platform under both symmetric and asymmetric information regimes, comparing the results to underscore the key novelties of the findings in relation to information asymmetry theory, particularly in addressing congestion effect in two-sided markets.

Keywords congestion; network effect; monopoly platform; information asymmetry

JEL Classification codes D21, D42, L22

1. Introduction

The present age witnessed a rapid rise of the platform economy due to meteoric spread of internet access and mobile devices. This business structure thrives on facilitating interactions between two distinct user groups through online platforms such as e-commerce marketplaces, ride-hailing services, and social media platforms (Rochet and Tirole 2003; Armstrong 2006; Poddar et al. 2022; Abe and Zennyo 2023). Lower transaction costs and the convenience of anytime, anywhere access have been key drivers of its global popularity. In fact, retail e-commerce sales are expected to exceed 6.3 trillion U.S. dollars globally in 2024, with continued growth projected in the coming years. [1]

Due to the unique characteristics of the platform economy, distinct from traditional market ecosystems, it's imperative to develop business models specifically tailored to this new environment. Researchers like Rochet and Tirole (2003), Armstrong (2006), Caillaud and Jullien (2001, 2003) recognized this need and laid the groundwork for analyzing platform markets as separate structures. Bai et al. (2022) noted that in a platform ecosystem, buyers usually consider a small subset of sellers while choosing their products, thereby excess number of sellers competing for buyers' attention may lead to market congestion. Sokullu (2023) also pointed out that contrary to the existing belief consumers' demand may not increase with more number of sellers. The platform hosting variety of sellers also can face asymmetric information regarding types of sellers. To mitigate the challenges of seller heterogeneity, the online marketplaces are adopting various strategies. Flipkart.com in India employs a 'Flipkart Assured' badge to distinguish high-quality sellers who meet specific quality and delivery standards. These sellers likely represent a registered

[1] Reported at https://www.statista.com/topics/871/online-shopping/#topicOverview

seller base that adheres to platform guidelines. However, Flipkart also hosts sellers who do not possess this badge. These may be sellers offering products of potentially lower quality or with less reliable delivery. In line with this, Amazon in India adopts Amazon Buy box[2], or Amazon's choice[3] listing of sellers to signal their credibility. However, there are loads of sellers in Amazon platform that do not receive these types of listing, and platforms cannot exactly identify the reputability of all these sellers. The issue of existence of too many sellers along with the sellers of low repute under asymmetric information may actually reduce consumer's satisfaction over purchase from the e-commerce platform. This issue has motivated us to delve into this present theoretical study. Our research deals with a specific platform scenario where platforms may encounter two distinct types of sellers when allowing them to transact in their marketplace. The presence of high-type ("h" type) sellers (they may be part of a registered/verified seller base, ensuring a certain level of quality) and low-type ("l" type) sellers (or, unregistered sellers with dubious reputation) in the same marketplace leads to an adverse selection problem as platforms cannot distinguish the types of the sellers at the entry level. We assume marginal gain a seller receives by supplying per unit of quality is higher for 'h' type seller compared to that of 'l' type sellers. We further assume that buyers have perfect information about seller quality through product reviews and ratings.[4] Despite the vast array of products available online, consumers often consider a limited subset of options (Bai et al. 2022). This phenomenon, known as bounded rationality, can lead to market congestion as the number of sellers increases. With more sellers comes with a greater variety of products, making it more challenging for buyers to filter through and find the exact match they're seeking.

[2] https://tinuiti.com/blog/amazon/win-amazon-buy-box/

[3] https://www.amazon.com/b?ie=UTF8&node=21449952011

[4] These reviews and ratings provide buyers with valuable information about the quality of products offered by individual seller. Although Bai et al. (2022) has noted that such ratings can be noisy, we will focus on the assumption of perfect information for buyers for the purposes of this study, as analyzing the impact of rating noise is beyond our current scope.

This problem is exacerbated by the presence of unregistered or low-quality sellers, who may further clutter the marketplace and hinder the buyer's search process. While prior research has extensively explored the positive network externalities that each side of a platform market generates for the other side, the impact of (negative) congestion effects has been largely overlooked or understudied in the existing literature. However, the impact of congestion effects, where a large seller base can lead to consumer choice overload, resulting in delay-related disutility (dissatisfaction caused by delays) has received less attention in the literature. Incorporating this critical aspect into our model, we posit that consumers consider not only platform fees and positive network benefits but also the negative effects of congestion. While researches by Fekih Romdhane et al. (2020), Aloui and Jebsi (2011), Poddar and Banerjee (2024), Wang, Ma and Xu (2017), Zhong et al. (2020), Yuan et al. (2024) have addressed congestion within their frameworks, our work builds upon this foundation by examining the combined effects of congestion and information asymmetry within a platform ecosystem. The effect of information asymmetry in the presence of network and congestion effect on key variables in a platform ecosystem is our major contribution to the existing literature. To the best of our knowledge, no prior research has examined their interplay within a two-sided platform. Our work fills this critical gap by investigating how congestion and information asymmetry interact to influence platform fees on both sides.

We focus on meeting the following key research objectives:

- To determine the equilibrium fees for both platform sides and the quality levels offered by different seller types under both information asymmetry and complete information scenarios (also coined as benchmark case or first-best case).

- To understand the influence of information asymmetry on platform behavior, we compare the platform strategies and resulting equilibria under information asymmetry and complete information scenarios.

The key insights of our research is manifold and can be summarized in a few points. First, when positive network effects outweigh congestion effects, the optimal strategy for a monopoly platform is to charge no fees to sellers under no asymmetry case. Conversely, when congestion outweighs positive network effects, to address congestion's negative consequences, the platform implements positive revenue-sharing fees for sellers to mitigate buyers' disutility caused by high congestion due to large number of sellers. Second, under information asymmetry, with a weaker congestion effect compared to positive network effects, the platform charges no fees to low-type sellers and a positive revenue-sharing fee for high-type sellers. Further, the quality differentiation leads to price discrimination where the platform charges higher membership fees for buyers purchasing from high-type sellers compared to those buying from low-type sellers. Third, in contrast to the scenario with weaker congestion under information asymmetry, when congestion effects outweigh positive network effects, the platform charges positive revenue-sharing fees to low-type sellers. Next, we analyze how changes in network and congestion coefficients affect fees. Compared to the ideal scenario with perfect information (first-best case), the platform offers lower revenue-sharing fees to high-type sellers leading to upward distortion in profit in the form of information rent when uncertain about seller types (second-best case). Conversely, low-type sellers pay higher revenue-sharing fees under information asymmetry compared to perfect information.

Our paper is organized as follows: Section 1 lays the technical foundation for our research problem. Section 2 provides a comprehensive review of relevant literature in this field. Section 3 discusses the research problem in detail and develop models for complete information and asymmetrical information regimes under a congestion scenario. Analytical results are presented for these models. In Section 4, we compare the optimal outcomes obtained under two scenarios discussed on previous section. Section 5 summarizes the key findings and contributions of our research. The mathematical proofs for the models are provided in the appendix.

2. Literature Review

This research draws on two key areas of the literature. While a vast body of research explores network externalities in two-sided platforms, the impact of congestion effects has received scant attention. Some recent works (such as Zhong et al. 2020; Poddar and Banerjee 2024; Bernstein et al. 2021; Aloui and Jebsi 2010, 2011; Fekih Romdhane et al. 2020; Yuan et al. 2024) have begun to explore congestion from different perspectives, laying the groundwork for our current research. The research by Zhong et al. (2020) investigates how on-demand service platforms can optimize their pricing and wage decisions to maximize profit while considering the presence of heterogeneous (diverse) customers with varying sensitivities to congestion. This allows them to compare the model that doesn't consider customer heterogeneity. The research assesses the performance of both models from the perspectives of all participants (platform, service providers, and customers) and society as a whole. Poddar and Banerjee (2024) consider both network effects and congestion effects in their model while discussing the hybrid role of a monopoly platform. Their model assumes network benefits to consumers increase with the number of sellers, but this growth is offset by congestion when there is a large seller base. Our study builds on this framework with a key distinction: we incorporate information asymmetry into the system. This allows us to investigate how the interplay of information asymmetry and congestion influences platform fees on both sides. In their work, Bernstein et al. (2021) analyze the effect of competition within the sharing economy. They incorporate congestion effects into their model by considering the relative number of consumers and drivers in the platform eco-system, both under single-homing (drivers working for one platform) and multi-homing (drivers working for multiple platforms) scenarios. Aloui and Jebsi (2010) investigate optimal pricing strategies for two-sided monopoly platforms where congestion affects only the buyer side. This congestion depends on the number of buyers and the platform's (fixed) capacity for buyers. Their analysis revealed two key findings: the optimal pricing strategy (divide-and-conquer) for the monopoly platform depends not only on the relative price elasticity of demand between the two sides (buyers and sellers) but also on the marginal congestion cost. Interestingly, the per-transaction fee charged to sellers is also influenced by the marginal congestion cost, even though sellers themselves are not directly affected by congestion. Aloui and Jebsi (2011) investigate how congestion effects on both sides of a two-sided duopoly platform influence platform pricing strategies. Their findings reveal that congestion leads to softened competition between platforms. Additionally, the traditional "divide-and-conquer" pricing strategy used by platforms is altered. This modification depends on the difference in the marginal congestion costs experienced by each side. The study by Fekih Romdhane et al. (2020) examines the implications of non-net neutrality within a two-sided congested monopoly platform. In this context, congestion arises due to the overuse of the platform's fixed bandwidth by content providers on one side of the market. Yuan et al. (2024) propose a two-sided market model that incorporates both established (original) and emerging businesses. They further explore how investment in research and development (R&D) by new business can influence its strategy in an environment characterized by network effects and own-side congestion effects. The study investigates optimal pricing strategies and profit potential for both types of businesses.

The second strand of literature delves into information asymmetry within the platform economy. Compared to the extensive research on information asymmetry within supply chains, relatively few studies have explored this issue in two-sided markets. Jeon et al. (2022) examine a two-type user model on the value creation side. They differentiate users based on a quality screening instrument and analyze both first-best and second-best equilibria in terms of user types. Subsequently, they extend the model by incorporating user heterogeneity on both sides of the platform. Jeon et al. (2015) investigate price discrimination strategies employed by a monopolistic two-sided platform facilitating interactions between distinct agent groups. Mukhopadhyay et al. (2008) examine optimal contract design under information asymmetry in a mixed-channel setting. The firm utilizes both a traditional manufacturer-retailer channel and a direct channel to consumers, which can threaten retailers and lead to channel conflict. To mitigate this, the model allows retailers to differentiate their offerings by adding value to the product. However, the manufacturer has limited information about the retailer's cost of adding value. Roger and Vasconcelos (2014) examine how a two-sided platform should set prices when sellers might engage in moral hazard.

Our comprehensive review of the literature reveals a critical research gap. The existing literature does not discuss the how the two-sided platforms chooses its key variables in the presence of information asymmetry regarding the types of sellers, while consumers experience congestion effect due to presence of too many sellers in the platform. The issue is important because with buyer side experiencing negative network effect in terms of congestion due to many sellers, the existence of asymmetric information on the part of the platform regarding types of seller leading to infiltration of sellers of dubious reputation may actually harm both buyers as well as the platform. Hence to address this gap, we investigate how platform fees are determined when both congestion and information asymmetry are present. Our research employs a two-step approach. We establish a benchmark model representing a first-best scenario with perfect information (no asymmetry) to serve as a baseline. This model allows us to analyze the effects of congestion on platform fees in an ideal setting. We then extend the model to incorporate information asymmetry, where the platform lacks complete knowledge about the marginal gain sellers receive for their products. This allows us to examine how fee determination changes under asymmetric information and how congestion interacts with this asymmetry in influencing fees on both sides (buyers and sellers). By comparing the outcomes of these two models, we aim to focus on how platform fees are structured when both congestion and information asymmetry are at play.

3. The model and agents

We present a monopoly two-sided platform framework following the one modeled by Rochet and Tirole (2003). Our model focuses on facilitating interactions between two distinct user groups: buyers (defined as B) and sellers (denoted as S) through an intermediary. While adopting the foundational framework of Rochet and Tirole (2003), we extend the model to address the critical issues of congestion and information asymmetry prevalent in platform ecosystems. We begin by analyzing the pay-offs for each group of agent on the platform and derive the market equilibrium under a benchmark scenario where there is no information asymmetry. Subsequently we extend this benchmark model by introducing the information asymmetry experienced by the monopoly platform. We then compare the results under both scenarios, all within the context of cross one-way congestion. [5]

[5] We here adopt the notion of one-way congestion where the congestion-related disutility primarily stems from a larger seller size on buyers, rather than the other way around.

3.1. Benchmark setup: Congestion with no information asymmetry

Platform Supply

The supply side of monopoly platform is generated by the population of sellers who can be of two types depending on marginal benefit received by selling one more unit of a i[th] quality (i.e., q_i) product, indexed as ϕ^i (where i denotes the type of the seller , $\forall$ i = h, l). By our assumption, $\phi^h > \phi^l$ if $q_i = \bar{q}, \forall$ i = h, l, indicating that high-type seller (denoted as h-type) receives greater additional revenue compared to low-type seller (presented as l-type) when each seller produces a product with $\bar{q}$ level of quality. A rationale behind this assumption may be that a group of sellers may have efficient technology that converts one unit of quality production to higher revenue earning vis-à-vis the inefficient group with lower ϕ^l. Further for simplicity we assume, $\text{Prob}(\phi^h) = \text{Prob}(\phi^l) = \frac{1}{2}$. Sellers of i type pay a part of the revenue received (indexed as α_i) to the platform to access platform's customer base. Investment in quality incurs a fixed cost, K_i for each seller-type i, drawn from a uniform distribution on the support $[0, \overline{K_i}]$. This cost reflects heterogeneity among sellers. Additionally, sellers incur a quadratic variable cost component; variable cost is increasing with sellers' investment on quality, denoted by $\frac{\beta q_i^2}{2}$, $\beta > 0$ is the cost co-efficient. Considering these factors, the profit of the seller of type i earns by participating on the platform, is represented by,

$$\pi_i^s = \begin{cases} (1-\alpha_h)\phi^h q_h - \frac{\beta q_h^2}{2} - K_h & \textit{when type } i = h \\ (1-\alpha_l)\phi^l q_l - \frac{\beta q_l^2}{2} - K_l & \textit{when type } i = l \end{cases} \tag{1}$$

Platform Demand

Consumers' perceptions of product quality influence their willingness-to-pay, hence a continuum of consumers can be defined by a valuation parameter, θ, distributed uniformly over the interval $[\underline{\theta}, \bar{\theta}]$. Here, the total number of buyers is normalized to 1. We assume that the quality of service (exogenous, here) provided by the platform is contingent on the quality of the seller with whom the buyer interacts. Buyers who purchase from high-quality sellers (or premium brands) are more likely to receive high-quality services (denoted as s_h) from the platform. Conversely, buyers who purchase from low-quality sellers are more likely to receive low-quality services (s_l). This implies that the platform operates in a two-tiered fashion, offering differentiated levels of service based on the seller's quality. [6] [7]A buyer's utility from requesting a purchase from the i^{th} seller on the platform is a function of three factors: (a) the valuation they place on the product quality offered by the i^{th} seller and type-contingent service quality received from the platform; (b) the type-contingent membership fee p_i^B paid by consumers to access platform's (differentiated) services; (c) the network externality derived from all the sellers participated on the platform. [8] Therefore, the expected utility of a buyer interacting with i^{th} type seller on the platform is presented as,

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[6] The platform's differentiated service levels based on seller quality can be seen as a form of discrimination. In case of information asymmetry, this discrimination is likely based on the information the platform acquires through the revenue-sharing contract at the entry point, which reveals the seller's type.

[7] To illustrate the concept of two-tiered service levels, we can revisit the example of Flipkart.com. The platform offers express delivery or one-day delivery services to buyers who purchase from F-Assured sellers. In contrast, buyers who purchase from non-F-Assured sellers typically receive standard delivery options. While we acknowledge the existence of exceptions where some non-F-Assured sellers may occasionally qualify for express delivery, the percentage of such cases is relatively low. Including these possibilities would introduce additional complexity in our model that could divert our attention from the core relationship between congestion and information asymmetry. To maintain the simplicity of our model, we only focus on the two primary tiers of service: express delivery for F-Assured sellers and standard delivery for non-F-Assured sellers.

[8] We assume that buyers on the platform receive a network externality primarily based on the total number of sellers, regardless of the specific type of seller they interact with. This is because buyers can freely explore and visit both F-Assured and non-F-Assured sellers within the Flipkart marketplace.

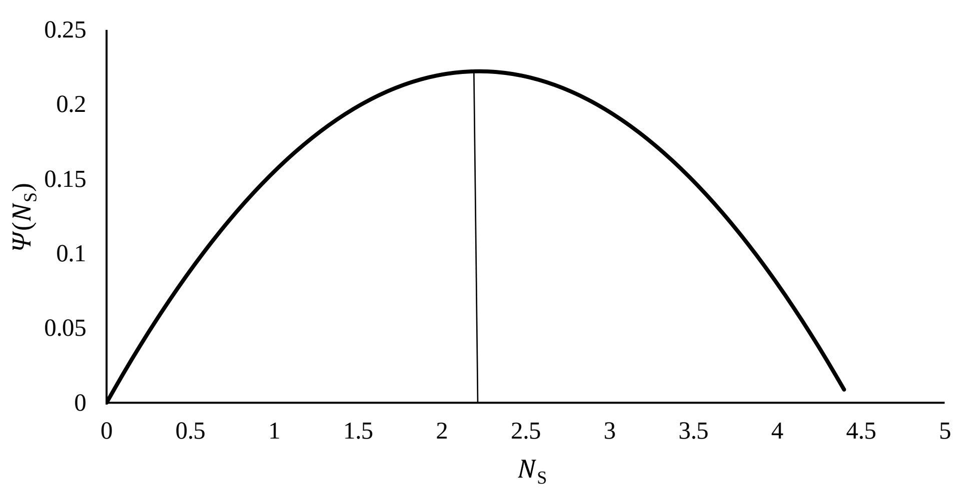
$$u_i = \begin{cases} \theta q_h + s_h - p_h^B + \Psi(N_s) & if\ interacts\ with\ type\ i = h \\ \theta q_l + s_l - p_l^B + \Psi(N_s) & if\ interacts\ with\ type\ i = l \end{cases} \tag{2}$$

where $\Psi(N_s)$ is network externality affecting buyers purchasing from i[th] seller on the platform. Mathematically, we take an inverse U-shaped network externality functional form as, $\Psi(N_s) = aN_s - bN_s^2$, where, a is the co-efficient associated with the positive network effect; a higher number of sellers translates to a benefit for consumers by increasing product variety. However, this can be offset by congestion on sellers' side. As noted by Poddar and Banerjee (2024), Sokullu (2023), consumers' demand is not monotonically increasing with the (network) seller size. In fact, excess of sellers can lead to a fall in consumer benefit. This adverse effect is often associated with congestion, which manifests as delays and increased search costs for consumers as they navigate through a vast number of options. To capture this negative impact, we introduce b, a co-efficient associated with the disutility generated by congestion (or degree of concavity of the network function).

For $a > 0$ and $b > 0$, $\Psi(N_s) > (\leq) 0$ for $N_s < (\geq) \overline{N_s}$ with $\overline{N_s} = \frac{a}{b}$. It is straightforward to verify that when N_s exceeds the threshold, $\overline{N_s}$, congestion inevitably occurs. Approaching the analysis differently, the "marginal network effect" that an additional seller exerts on side B can be expressed as follows, $\frac{\partial u_i(N_s)}{\partial N_s} = \frac{\partial \Psi(N_s)}{\partial N_s} = a - 2bN_s\ \ \forall$ i = h, l. Assuming $a > 0$ and $b > 0$, we easily show that $\frac{\partial \Psi(N_s)}{\partial N_s} = a - 2bN_s \geq (<)\ 0$ for $N_s \leq (>)\ \widehat{N_s} = \frac{a}{2b} \in [0, \overline{N_s}]$ and $\Psi''(N_s) < 0$. We can assume that when $N_s \leq \widehat{N_s}$, the (net) network externality is positive and increasing in the seller size up to $N_s = \frac{a}{2b}$. In this zone, consumers benefit from being part of a (growing) seller network. We call this as positive network effect when $N_s \leq \widehat{N_s}$.

The network benefit, $\Psi(N_s)$ reaches its peak (i.e., $\frac{a^2}{4b}$) at $N_s = \widehat{N_s} = \frac{a}{2b}$. Beyond this point, the externality benefit declines as the number of sellers increases up to $\overline{N_s} = \frac{a}{b}$. As a result, consumers are worse off when the platform becomes overly crowded with sellers. While a growing seller network initially benefits consumers, excessive seller participation can lead to consumer disutility. When the number of sellers exceeds $\widehat{N_s}$, the negative effects of congestion outweigh the positive benefits, resulting in a decline in consumer network benefit. We refer to this phenomenon as the congestion effect when $N_s > \widehat{N_s}$. Beyond $N_s = \overline{N_s} = \frac{a}{b}$, the externality becomes negative, indicating that consumers network benefit is negative due to the excessive congestion caused by an excessive number of sellers. To focus on the positive impact of the network externality, we restrict our analysis to the range $0 < N_s \leq \overline{N_s}$. This ensures that we are operating within the positive externality regime and avoid the negative consequences of excessive congestion. Based on the aforementioned assumptions, we assume $0 < N_s \leq 4.4$, a range where $\Psi(N_s) > 0$. We then plot $\Psi(N_s)$ as a function of N_s. Figure 1 explains the inverted U-shaped network externality function.

Fig. 1: The network externality function



Monopoly Platform

The monopoly platform acts as a marketplace, fostering interactions between its two distinct user groups: buyers and sellers. It generates revenue through two types of fees: membership fees paid by buyers for the privilege of accessing the platform and its sellers and revenue-sharing fees paid by sellers as a percentage of their sales on the platform. [9] Equation (3) defines the expected profit of the monopoly platform.

$$\Pi_P = \frac{1}{2}(p_h^B D_h + \alpha_h \Phi^h q_h N_h^S) + \frac{1}{2}(p_l^B D_l + \alpha_l \Phi^l q_l N_l^S) \tag{3}$$

where D_h and D_l are the expected number of consumers purchasing from high-type and low-type sellers respectively; N_h^S and N_l^S are the expected size of high and low-type sellers respectively.

Market Equilibrium under symmetrical information

In this section, we assume the monopoly platform has perfect information about the type of each seller (h or l). This allows us to derive the first-best solution, which represents the most efficient outcome for the entire market (platform, sellers, and buyers) under these ideal conditions. Our model analyzes a sequential decision-making process. First, the monopoly platform sets fees for both buyers and sellers. Second, sellers decide whether to participate on the platform and, if so,

[9] To reflect real-world practices, our model incorporates a fee structure commonly observed in two-sided platforms. In many cases, platforms charge buyers a fixed membership fee (e.g., Amazon Prime membership), eliminating the need for payment of additional fee each time they make a transaction. This approach is consistent with the work of researchers like Poddar and Banerjee (2024), Kim (2014), Xue et al. (2019). On the seller side, platforms often charge a percentage-based fee on the selling price of the product. This structure is exemplified by referral fees commonly encountered on platforms like Amazon. We adopt this combined fee structure (fixed subscription fee for buyers, percentage-based revenue-sharing fee for sellers) to ensure our model closely resembles real-world scenarios.

what quality level to offer. Finally, buyers decide whether to participate on the platform given the fees and seller decisions. We solve this game using backward induction.

Participation decisions by consumers

A consumer purchases from a high-type seller if $u_h > u_l$. The expected number of such consumers will be, $D_h = \frac{1}{(\overline{\theta}-\underline{\theta})}\left[\overline{\theta} - \frac{\{(p_h^B-p_l^B)-(s_h-s_l)\}}{q_h-q_l}\right]$

The expected number of consumers who will purchase from low-quality seller is,

$$D_l = \frac{1}{(\overline{\theta}-\underline{\theta})}\left[\frac{\{(p_h^B-p_l^B)-(s_h-s_l)\}}{q_h-q_l} - \frac{p_l^B-s_l-\Psi(N_s)}{q_l}\right]$$

Thus, the buyers' market is partially covered. Total number of consumers,

$$N_B = \frac{1}{(\overline{\theta}-\underline{\theta})}\left[\overline{\theta} - \frac{p_l^B-s_l-\Psi(N_s)}{q_l}\right]$$

Quality choice and participation decisions by sellers

In order to maximize their profits, sellers of each type will strategically choose the optimal quality level for their product. Thus, differentiating the profit equation of high type seller and setting it equal to zero, we derive, ${q_h}^* = \frac{(1-\alpha_h)\phi^h}{\beta}$. Substituting ${q_h}^*$ in the profit of high-type, we obtain,

$\pi_h^S = \frac{(1-\alpha_h)^2{\phi^h}^2}{2\beta} - K_h \geq 0$ where $K_h \in [0, \overline{K_h}]$ (here, we assume that each seller i earns zero profit from using the outside option)

The number of high-type seller is obtained as, $N_h^S = \frac{1}{\overline{K_h}}\left[\frac{(1-\alpha_h)^2{\phi^h}^2}{2\beta}\right]$

By repeating this analysis for low-type sellers, we obtain, ${q_l}^* = \frac{(1-\alpha_l)\phi^l}{\beta}$ and $N_l^S = \frac{1}{\overline{K_l}}\left[\frac{(1-\alpha_l)^2{\phi^l}^2}{2\beta}\right]$

Total number of seller, $N_S = N_h^S + N_l^S = \frac{1}{2\beta}\left[\frac{(1-\alpha_h)^2 \phi^{h^2}}{\overline{K_h}} + \frac{(1-\alpha_l)^2 \phi^{l^2}}{\overline{K_l}}\right]$

Monopoly platform's strategy for optimal fees

In the final stage, we substitute the optimal values for quality levels and number of agents determined in earlier stages into the platform's profit function.

By maximizing the profit equation of the monopoly platform (as outlined in (3)), we can derive the optimal fees that the platform charges on both sides of the market. [10] The optimal fee structure for the platform is contingent upon the network externality function. In regions $(0 \leq N_s \leq \widehat{N_s})$ where the positive network externality dominates (i.e., $\frac{\partial \Psi(N_S)}{\partial N_s} > 0$), we derive $\frac{\partial \Psi(N_S)}{\partial \alpha_h} = \underbrace{\frac{\partial \Psi(N_S)}{\partial N_s}}_{+}\underbrace{\frac{dN_s}{d\alpha_h}}_{-} < 0$ and $\frac{\partial \Psi(N_S)}{\partial \alpha_l} = \underbrace{\frac{\partial \Psi(N_S)}{\partial N_s}}_{+}\underbrace{\frac{dN_s}{d\alpha_l}}_{-} < 0$. For $\widehat{N_s} < N_s \leq \overline{N_s}$, where the negative congestion effect dominates (i.e., $\frac{\partial \Psi(N_S)}{\partial N_s} < 0$) and eventually network curve declines however, is positive, we derive $\frac{\partial \Psi(N_S)}{\partial \alpha_h} = \underbrace{\frac{\partial \Psi(N_S)}{\partial N_s}}_{-}\underbrace{\frac{dN_s}{d\alpha_h}}_{-} > 0$ and $\frac{\partial \Psi(N_S)}{\partial \alpha_l} = \underbrace{\frac{\partial \Psi(N_S)}{\partial N_s}}_{-}\underbrace{\frac{dN_s}{d\alpha_l}}_{-} > 0$. The (net) network effect on buyers has a non-monotonic relationship with proportion of revenue paid to the platform by sellers. As the platform's revenue share increases, fewer sellers are likely to join the platform. This, in turn, can lead to a decrease in buyer benefit due to product variety. However, this relationship can reverse when the number of sellers exceeds a critical threshold, $\widehat{N_s}$ (i.e., in the region where $\frac{\partial \Psi(N_S)}{\partial N_s} < 0$). Beyond this point, increasing the platform's revenue share can actually improve buyer network benefit. This is because a higher revenue share can dis-incentivize excess seller participation, alleviating congestion.

[10] For detailed calculations, please refer to the Appendix A.

Therefore we draw two cases. Case 1 relates the optimal fees when congestion effects falls short of the positive network effects ($\frac{\partial \Psi(N_s)}{\partial N_s} > 0$) and we call it case 2 when congestion effect dominates the positive network effect thus $\frac{\partial \Psi(N_s)}{\partial N_s} < 0$.

Case I ($0 \leq \boldsymbol{N_s} \leq \widehat{\boldsymbol{N_s}}$): $\frac{\partial \Psi(N_S)}{\partial \alpha_h} < 0 \ and \ \frac{\partial \Psi(N_S)}{\partial \alpha_l} < 0$; We obtain a solution of $(\alpha_{h1}{}^{*}, \alpha_{l1}{}^{*}) \equiv (0,0)$ [11]

In the scenario where the positive network benefit is higher than the congestion effect, we find that the platform optimally charges no revenue-sharing fee to sellers. In regions where the network externality is rising, an additional seller can yield additional utility to buyers. This is because buyers in these regions derive positive benefits from each additional seller joining the platform. To attract more sellers and capitalize on this positive externality, platforms may adopt a zero revenue-sharing fee strategy. By eliminating fees, platforms can incentivize more sellers to join the platform, further enhancing the network effect and benefitting buyers. The equilibrium solutions for buyers' membership fees can be expressed as follows,

$$p_{l1}^{B*} = \frac{\bar{\theta}\phi^{l}}{2\beta} + \frac{1}{2}[s_l + \Psi(N_{S1}{}^{*})], \ p_{h1}^{B*} = \frac{\bar{\theta}\phi^{h}}{2\beta} + \frac{1}{2}[s_h + \Psi(N_{S1}{}^{*})] \ \text{ where, } N_{S1}{}^{*} = \frac{1}{2\beta}\left[\frac{{\phi^{h}}^{2}}{\overline{K_h}} + \frac{{\phi^{l}}^{2}}{\overline{K_l}}\right]$$

Case II ($\widehat{\mathbf{N_s}} < \mathbf{N_s} \leq \overline{\mathbf{N_s}}$): $\frac{\partial \Psi(N_S)}{\partial \alpha_h} > 0 \ and \ \frac{\partial \Psi(N_S)}{\partial \alpha_l} > 0$; we get a unique (interior) first-best equilibrium$(\alpha_{h2}{}^{*}, \alpha_{l2}{}^{*})$.

The optimal fee structure changes when congestion effects become more dominant. In such cases, the platform needs to address the negative consequences of congestion. To mitigate the disutility originating due to the higher congestion for buyers side, the platform implements positive revenue-

[11] Superscript * represents the first best solution when the platform knows the seller type and subscript "1" signifies the case I problem.

sharing fees for sellers. This approach encourages sellers to optimize their behavior and potentially reduce congestion, ultimately improving the overall user experience. The buyers' membership fees are given by, $p_{l2}^{B*} = \frac{\bar{\theta}(1-\alpha_{l2}{}^{*})\phi^{l}}{2\beta} + \frac{1}{2}[s_l + \Psi(N_{S2}{}^{*})]$, $p_{h2}^{B*} = \frac{\bar{\theta}(1-\alpha_{h2}{}^{*})\phi^{h}}{2\beta} + \frac{1}{2}[s_h + \Psi(N_{S2}{}^{*})]$

3.2. Congestion with information asymmetry

We extend the benchmark model to investigate how the platform's strategy changes when information asymmetry regarding seller types is introduced. In the benchmark model, the platform possesses perfect information about seller types. However, in the extended model, we consider a scenario where the platform cannot perfectly monitor the sellers' types and thus cannot distinguish between high-type and low-type sellers.

Changes in the setting

The sequential decision-making process is analyzed using backward induction. The platform initiates the process by offering a menu of contracts consisting of fees to a seller of type i. The seller then selects a specific contract and then determines the product quality to offer. This choice of contract effectively reveals the seller's type i. Finally, buyers make their participation decisions.

To encourage truthful revelation of seller types, we introduce a constraint known as incentive compatibility (IC). This constraint ensures that a seller always earns a higher profit by reporting their true type (high or low) and choosing the fee associated with that type. In other words, it discourages sellers from misrepresenting their type to gain an unfair advantage. Because IC constraints directly influence seller profits, the platform's optimization process changes significantly compared to the benchmark model. We formalize a constrained optimization problem, as shown below,

$$\Pi_P = \frac{1}{2}(p_h^B D_h + p_l^B D_l + \alpha_h \phi^h q_h N_h^S + \alpha_l \phi^l q_l N_l^S)$$

Subject to,

IC_h: $$(1-\alpha_h)\phi^h q_h - \frac{\beta q_h^2}{2} - K_h \geq (1-\alpha_l)\phi^h q_l - \frac{\beta q_l^2}{2} - K_h$$

Or, $$\frac{(1-\alpha_h)^2 {\phi^h}^2}{2\beta} \geq \frac{(1-\alpha_l)^2 \phi^l (2\phi^h - \phi^l)}{2\beta}$$

IC_l: $$(1-\alpha_l)\phi^l q_l - \frac{\beta q_l^2}{2} - K_l \geq (1-\alpha_h)\phi^l q_h - \frac{\beta q_h^2}{2} - K_l$$

Or, $$\frac{(1-\alpha_l)^2 {\phi^l}^2}{2\beta} \geq \frac{(1-\alpha_h)^2 \phi^h (2\phi^l - \phi^h)}{2\beta}$$

The constraint indicated by IC_h guarantees that a high-type seller benefits from truthfully revealing their true type. This means the profit earned by reporting their high type (h) must be greater than the profit they would receive by misrepresenting themselves as a low-type seller. Similarly, the IC constraint applies to low-type sellers as indicated by IC_l. During the constraint identification process, we establish one claim that will be essential for solving the optimization problem.

Claim 1: If IC_h is binding then IC_l is satisfied and non-binding.

Building on claim 1, we can derive a reduced-form optimization problem which focuses on maximizing the platform's profit equation while incorporating the incentive compatibility (IC) constraint specifically for the high-type seller, IC_h.

We have, $\Psi(N_S) = aN_S - bN_S{}^2 = A\phi^l(1-\alpha_l)^2\left[a - bA\phi^l(1-\alpha_l)^2\right] > 0$

$$\frac{\partial\,\Psi(\mathrm{N_S})}{\partial\alpha_\mathrm{l}} = \frac{\partial\,\Psi(\mathrm{N_S})}{\partial \mathrm{N_S}}\frac{\mathrm{d}\,\mathrm{N_S}}{\mathrm{d}\alpha_\mathrm{l}} \lesseqgtr 0$$

In the rising portion of the externality curve (for the zone $(0 \leq \mathrm{N_s} \leq \widehat{\mathrm{N_s}})$, where $\frac{\partial\,\Psi(\mathrm{N_S})}{\partial \mathrm{N_S}} > 0$, we observe $\frac{\partial\,\Psi(\mathrm{N_S})}{\partial\alpha_\mathrm{l}} = \underbrace{\frac{\partial\,\Psi(\mathrm{N_S})}{\partial \mathrm{N_S}}}_{+}\underbrace{\frac{\mathrm{d}\,\mathrm{N_S}}{\mathrm{d}\alpha_\mathrm{l}}}_{-} < 0$. For the other zone, $(\widehat{\mathrm{N_s}} < \mathrm{N_s} \leq \overline{\mathrm{N_s}})$, where $\frac{\partial\,\Psi(\mathrm{N_S})}{\partial \mathrm{N_S}} < 0$, we have $\frac{\partial\,\Psi(\mathrm{N_S})}{\partial\alpha_\mathrm{l}} = \underbrace{\frac{\partial\,\Psi(\mathrm{N_S})}{\partial \mathrm{N_S}}}_{-}\underbrace{\frac{\mathrm{d}\,\mathrm{N_S}}{\mathrm{d}\alpha_\mathrm{l}}}_{-} > 0$. Depending on the relative magnitude of the network externality and the impact of congestion, the model can exhibit two different equilibria.

Proposition 1: In the two-state framework with information asymmetry where the single intermediary platform cannot distinguish seller types, and if congestion effect is weaker compared to the positive network effect, that is $\frac{\partial\,\Psi}{\partial\alpha_l} < 0$ *the optimal solution is given as follows:*

$$(\alpha_{h1}{}', \alpha_{l1}{}') = \left(1 - \frac{\sqrt{\phi^l(2\phi^h - \phi^l)}}{\phi^h}, 0\right); \tag{4}$$ [12]

$$p_{h1}^{B\prime} = \frac{\bar{\theta}\sqrt{\phi^l(2\phi^h - \phi^l)}}{2\beta} + \frac{1}{2}[s_h + \Psi(N_{S1}{}')]\,;\, p_{l1}^{B\prime} = \frac{\bar{\theta}\phi^l}{2\beta} + \frac{1}{2}[s_l + \Psi(N_{S1}{}')] \tag{5}$$

where $N_{S1}{}' = \frac{\phi^l}{2\beta}\left[\frac{2\phi^h - \phi^l}{\overline{K_h}} + \frac{\phi^l}{\overline{K_l}}\right]$

$$q_{h1}{}' = \frac{\sqrt{\phi^l(2\phi^h - \phi^l)}}{\beta};\; q_{l1}{}' = \frac{\phi^l}{\beta} \tag{6}$$

We obtain, $\alpha_{h1}{}' > \alpha_{l1}{}'$ if $[(\phi^h - \phi^l)^2] > 0$ for all $\phi^h > \phi^l$, high type firm would pay a higher proportion of its revenue. Moreover, $p_{h1}^{B\prime} > p_{l1}^{B\prime}$. [13] High-type sellers offer a higher level of quality

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[12] Superscript ʻ denotes the equilibrium values for second best solution when the platform cannot distinguish between two sellers.

[13] $(p_h^{B*} - p_l^{B*}) = \frac{\bar{\theta}\sqrt{\phi^l(2\phi^h - \phi^l)}}{2\beta} - \frac{\bar{\theta}\phi^l}{2\beta} = \frac{\bar{\theta}}{2\beta}\left[\sqrt{\phi^l(2\phi^h - \phi^l)} - \phi^l\right] > 0$ since $\phi^h > \phi^l$

compared to low-type sellers (i.e., $q_{h1}' > q_{l1}'$) . Since high-type sellers receive a greater additional revenue compared to low-type sellers ($\phi^{h} > \phi^{l}$) , they have a stronger incentive to invest in higher quality. Consequently, they are also willing to pay a higher revenue-sharing fee to the platform to access its customer base. From the buyer's perspective, the higher quality offered by high-type sellers translates into greater value. Therefore, consumers are prepared to pay a higher platform membership fee to access products from high-type sellers compared to those offered by low-type sellers.

We undertake comparative static analysis to investigate how the equilibrium fee structure of the monopoly platform changes in response to variations in the positive network coefficient (denoted by a) and the congestion-disutility coefficient (denoted by b). As the network effect strengthens (i.e., the positive network coefficient increases), the utility for consumers increases. Recognizing this, the platform strategically raises the fees it charges to buyers (Formally, we derive $\frac{dp_{h1}^{B\prime}}{da} > 0$; $\frac{dp_{l1}^{B\prime}}{da} > 0$). Conversely, a higher congestion-disutility coefficient, b reduces consumer utility. Consequently, the membership fees paid by consumers tend to decrease as b increases (we derive $\frac{dp_{h1}^{B\prime}}{db} < 0$; $\frac{dp_{l1}^{B\prime}}{db} < 0$). For the zone, $0 \leq \mathrm{N_s} \leq \widehat{\mathrm{N_s}}$ where the congestion effect is weak, neither a change in a nor a change in b has a significant impact on fees paid by sellers.

Our focus in the next scenario shifts to the second choice solution in the region, $\widehat{\mathrm{N_s}} < \mathrm{N_s} \leq \overline{\mathrm{N_s}}$ when the negative impact of congestion outweighs the positive network effects.

Proposition 2: In the two-state framework with information asymmetry where the single intermediary platform cannot distinguish seller types and there exists a strong congestion effect *compared to the network effect, that is* $\frac{\partial \Psi}{\partial \alpha_l} > 0$ *, the equilibrium revenue-sharing fee for low-type seller is positive, i.e.,* $\alpha_l{}' > 0$*.*

By employing $\mathrm{IC_h}$, we can express α_h as a function of α_l;

$$\alpha_h = \left[1 - \frac{(1-\alpha_l)}{\phi^h}\sqrt{\phi^l(2\phi^h - \phi^l)}\right]. \quad (7)$$

Substituting this expression for α_h into the profit equation allows us to represent the profit solely as a function of α_l. Therefore, we derive,

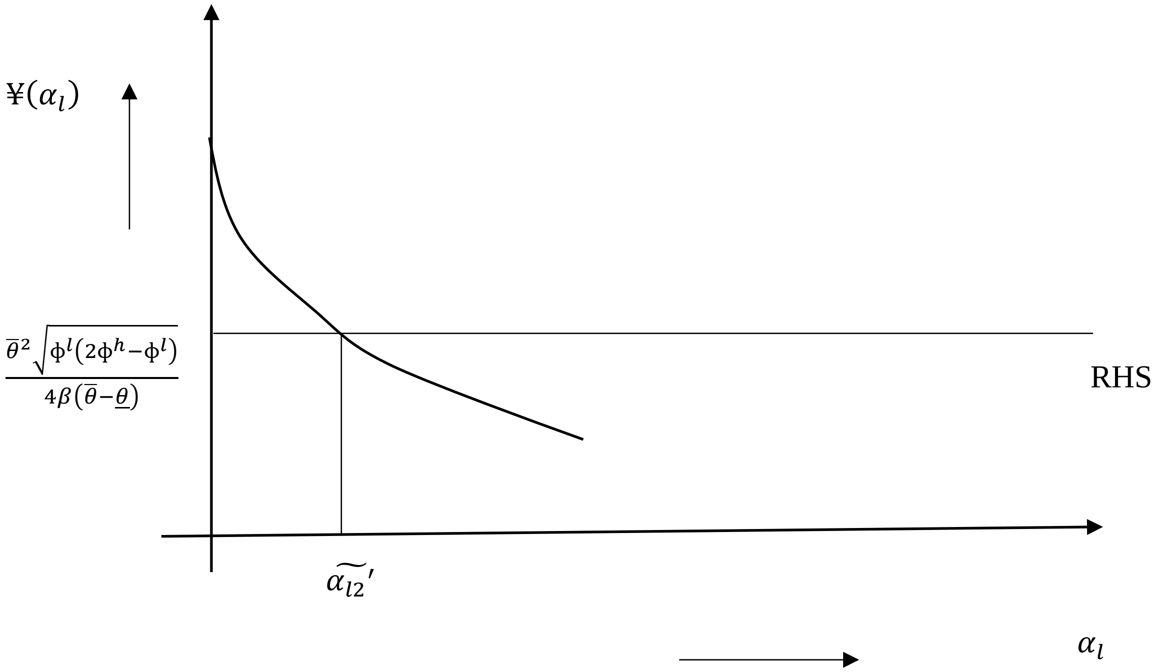
$$\Pi_P = \frac{1}{2}\left[\frac{1}{4(\bar{\theta}-\underline{\theta})}\left[\frac{\bar{\theta}}{\beta}\sqrt{\phi^l(2\phi^h - \phi^l)}(1-\alpha_l) + \{s_h + \Psi(N_S)\}\right]\left[\bar{\theta} + \frac{(s_h - s_l)\beta}{(1-\alpha_l)\left\{\sqrt{\phi^l(2\phi^h-\phi^l)} - \phi^l\right\}}\right] + \frac{1}{4(\bar{\theta}-\underline{\theta})}\left[\frac{\bar{\theta}(1-\alpha_l)\phi^l}{\beta} + \{s_l + \Psi(N_S)\}\right]\left[\frac{\beta\{s_l + \Psi(N_S)\}}{(1-\alpha_l)\phi^l} - \frac{(s_h - s_l)\beta}{(1-\alpha_l)\left\{\sqrt{\phi^l(2\phi^h-\phi^l)} - \phi^l\right\}}\right] + \frac{{\phi^h}^4}{2\beta^2\overline{K_h}}\left[1 - \frac{(1-\alpha_l)}{\phi^h}\sqrt{\phi^l(2\phi^h - \phi^l)}\right]\left[\frac{(1-\alpha_l)^3}{{\phi^h}^3}\{\phi^l(2\phi^h - \phi^l)\}^{\frac{3}{2}}\right] + \frac{{\phi^l}^4}{2\beta^2\overline{K_l}}\alpha_l(1-\alpha_l)^3\right]$$

By simplifying the profit equation and then differentiating with respect to, α_l, we obtain the first order condition as, $\frac{\partial \Pi_P}{\partial \alpha_l} = 0$

By simplifying the above equation, we obtain, $¥(\alpha_l) = \frac{\bar{\theta}^2\sqrt{\phi^l(2\phi^h - \phi^l)}}{4\beta(\bar{\theta}-\underline{\theta})}$ where $¥'(\alpha_l) < 0$. (8)

Thus, we derive, $\alpha_{l2}{}' = ¥^{-1}\left[\frac{\bar{\theta}^2\sqrt{\phi^l(2\phi^h - \phi^l)}}{4\beta(\bar{\theta}-\underline{\theta})}\right] = \widetilde{\alpha_{l2}}{}'$. Substituting the optimal value of α_l in equation (7), we derive, $\alpha_{h2}{}' = \left[1 - \frac{(1-\widetilde{\alpha_{l2}{}'})}{\phi^h}\sqrt{\phi^l(2\phi^h - \phi^l)}\right] = \widetilde{\alpha_{h2}}{}'$

Fig 2 Determination of revenue-sharing rate of low-quality seller



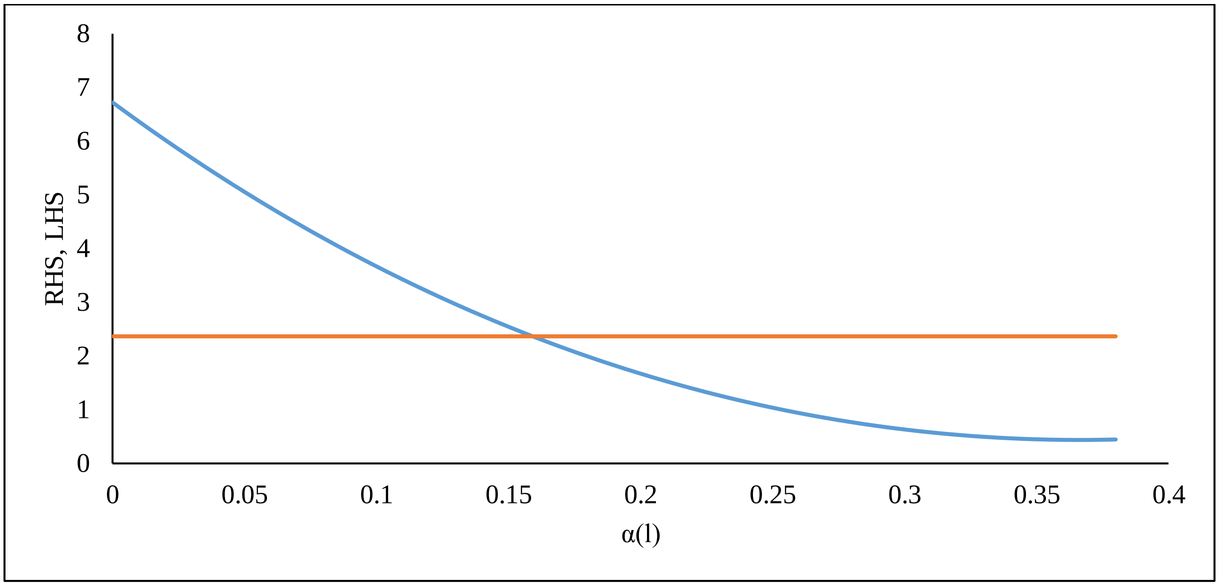
From the First Order Condition for profit maximization denoted by equation (8), we graph the LHS and RHS. LHS, denoted by $¥(\alpha_l)$ has a downward slope and the term on the RHS is constant, so it graphs as a horizontal line. Intersection between a downward sloping line and a horizontal line determines the unique optimal solution for α_l.

Source: Based on the theoretical model

Unlike the last case; with $\frac{\partial \Psi}{\partial \alpha_l} > 0$, the equilibrium value is $\widetilde{\alpha_{l2}}'$>0

We apply a numerical analysis to corroborate our analytical findings regarding the optimal fee structure. We achieve this by substituting specific values for the model's parameters as, $\phi^h = 2, \phi^l = 1, \beta = 0.5, \bar{\theta} = 2, \underline{\theta} = 1, \overline{K_h} = 1 = \overline{K_l}, a = 0.2, b = 0.045, s_h = 2, s_l = 1$.

Fig 3 Determination of revenue-sharing rate paid to platform by low-quality seller



Plotting the L.H.S and R.H.S of equation (8) for specific parameter values, we obtain an unique value of revenue-sharing rate for low-quality seller , $\alpha_{l2}{}' = 0.16$. The equilibrium revenue-sharing rates, $(\alpha_{h2}{}', \alpha_{l2}{}') = (0.27, 0.16)$.

Source: Numerical analysis based on theoretical model

Having established the second-best solution for the case (where $\frac{\partial\,\Psi}{\partial \alpha_l} > 0$) through both analytical and numerical methods, we now focus on analyzing how the network effect and congestion effect influence the equilibrium fees paid by both buyers and sellers to the platform under the scenario of a strong congestion effect compared to the positive network benefit, i.e., $\frac{\partial\,\Psi}{\partial \alpha_l} > 0$. The key findings from this sensitivity analysis are summarized in Proposition 3.

Proposition 3

(i) *The optimal revenue-sharing fees paid to platform decreases unambiguously if the network benefit co-efficient, a, increases (thus,* $\frac{d\alpha_{l2}{}'}{da} < 0$ *and* $\frac{d\alpha_{h2}{}'}{da} < 0$)

(ii) *The optimal revenue-sharing fees paid to platform increases unambiguously if the congestion-disutility co-efficient, b, increases (thus,* $\frac{d\alpha_{l2}'}{db} > 0$ *and* $\frac{d\alpha_{h2}'}{db} > 0$*).*

(iii) *The optimal membership fees paid by buyers increases as network benefit co-efficient increases (i.e., the value of the platform increases for buyers due to more sellers) (thus,* $\frac{dp_{l2}^{B\prime}}{da} > 0$ *and* $\frac{dp_{h2}^{B\prime}}{da} > 0$*)*

(iv) *The optimal membership fees paid by buyers tend to decrease as congestion-disutility co-efficient strengthens (thus,* $\frac{dp_{l2}^{B\prime}}{db} < 0$ *and* $\frac{dp_{h2}^{B\prime}}{db} < 0$*)*

The economic rationale behind these fee structures is straightforward. When consumers exhibit higher sensitivity to the positive network size, the threshold for a (net) positive network effect also increases. In response to an increase in a (which represents the sensitivity parameter), the network externality curve shifts upward, indicating that consumers are now more willing to transact with larger seller bases. As illustrated in Figure 4, when the sensitivity parameter increases from a to a_1, the seller size required to generate a positive network effect (i.e., $\Psi(N_s) > 0$) for buyers also expands. Specifically, the threshold for a net positive network effect rises from $\overline{N_s}\left(=\frac{a}{b}\right)$ to $\overline{N_s^1}\left(=\frac{a_1}{b}\right)$ when $a_1 > a$. To attract more sellers, the platform lowers the revenue-sharing fees (charged to sellers) when the positive network co-efficient is strong. Thus, $\frac{d\alpha_{l2}'}{da} < 0$ and $\frac{d\alpha_{h2}'}{da} < 0$. This incentivizes sellers to join the platform, thereby increasing the network effect. On the other hand, a stronger positive network (i.e., a higher "a") also translates into greater value for consumers. This allows the platform to raise the membership fees paid by buyers, who are willing to pay more to access the expanded platform and the benefits of a richer network. Therefore, we have, $\frac{dp_{l2}^{B\prime}}{da} > 0$ *and* $\frac{dp_{h2}^{B\prime}}{da} > 0$. Therefore, we can observe that the decisions made by the platform on one side are influenced by the actions of the other side. This interconnectedness is a defining feature of two-sided platforms, where the success of one side depends on the participation and engagement of the other.

Fig. 4 Modified Network externality function due to change in “a”

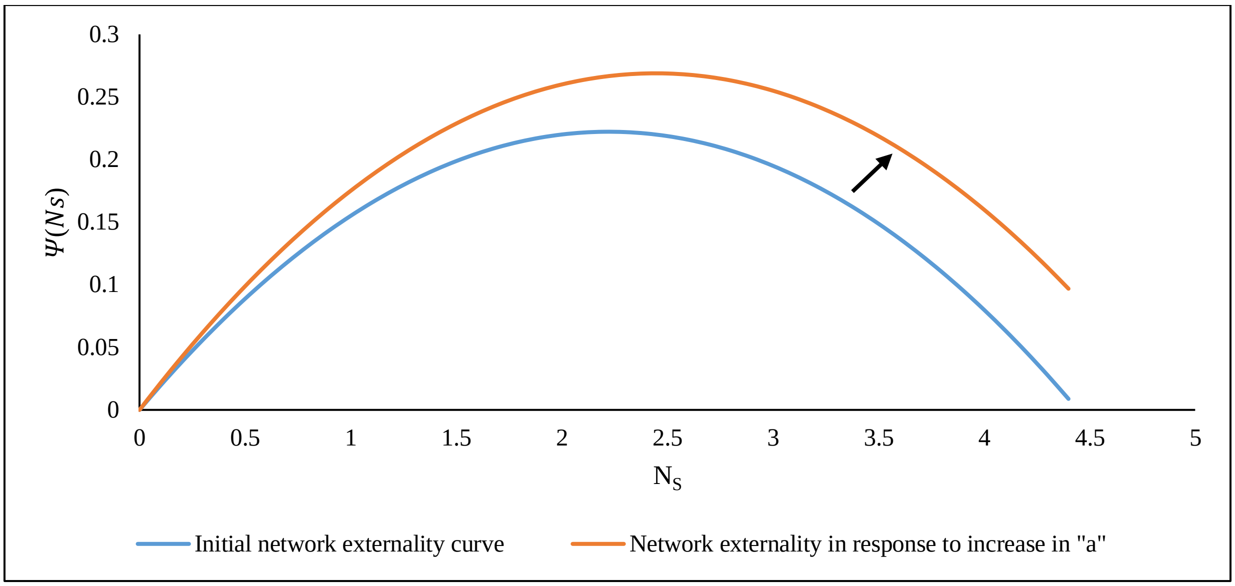
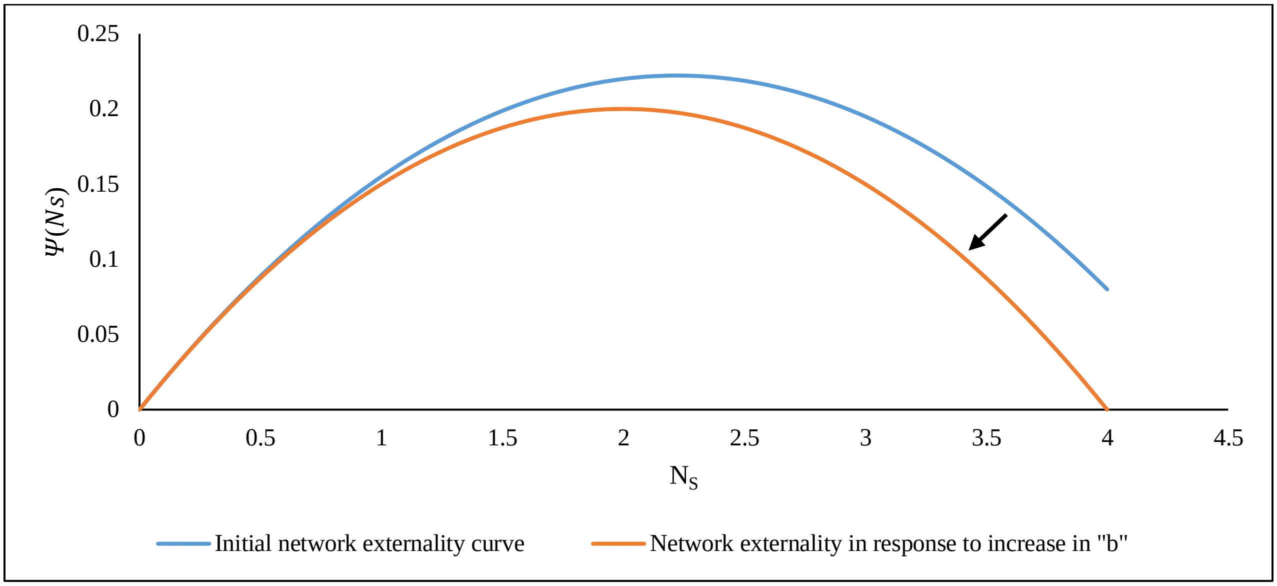


Fig 5 Modified network externality curve due to change in “b”



A higher congestion-disutility coefficient, b indicates a stronger negative impact on consumers due to congestion. To mitigate this disutility and maintain user satisfaction, the platform strategically reduces the membership fees paid by buyers. In other words, as b increases, the platform makes the platform more affordable for buyers to compensate for the decrease in utility they experience. Conversely, the platform tends to raise the revenue-sharing fees charged to sellers in response to a higher congestion coefficient. This is because excessive seller presence can exacerbate congestion, and the platform seeks to discourage sellers’ participation. Therefore, we derive $\frac{d\alpha_{l2}{'}}{db} > 0$ and $\frac{d\alpha_{h2}{'}}{db} > 0$. As depicted in Figure 5, when the parameter b increases, buyers become less willing to transact with a large number of sellers. This leads to a decrease in the net positive network effect they receive from a given seller size. As a result, the network curve shifts downward.

4. Discussion of Results

In the scenario with asymmetric information, where the platform cannot perfectly distinguish seller types, a high-type seller has an incentive to imitate a low-type seller if they are given with agreement similar to first best solution. This is because mimicking a low-type seller leads to a positive payoff for high type seller. To counteract this imitation and encourage truthful revelation, the platform strategically adjusts its fee structure by introducing IC. Specifically, compared to the complete information case where seller types are known, the platform implements a lower revenue-sharing fee to high-type seller in the presence of information asymmetry. This lower fee under information asymmetry incentivizes high-type sellers to reveal their true identity and participate on the platform. However, the revenue-sharing fee for low type seller is actually higher under information asymmetry compared to complete information case. Thus, ${\alpha_h}' < {\alpha_h}^*$ and ${\alpha_l}' > {\alpha_l}^*$.

Proposition 4: The revenue-sharing fee paid by high type seller is less when the platform is uncertain about seller type (i.e., the second-best solution) compared to the first-best case. On the other hand, the revenue-sharing fee paid by low type seller is higher when the platform is uncertain about seller type (i.e., the second-best solution) compared to the first-best scenario. Formally, we derive, ${\alpha_h}' < {\alpha_h}^*$ *and* ${\alpha_l}' > {\alpha_l}^*$*.*

Due to the lower revenue-sharing fee imposed on high-type sellers under information asymmetry, these sellers earn an expected profit that is strictly greater than their first-best profit. This is the information rent which represents the additional profit that high-type sellers capture due to their private information. Therefore, the optimal contract under asymmetric information results in upward distortions in the profits of high-type sellers. This finding aligns with the work of Jebsi and Thomas (2005) for a congestible network good in a one-sided market. To induce high-type sellers to reveal their true identity and participate on the platform, the platform is willing to pay this information rent (represented in terms of lower revenue-sharing fee paid to platform). To offset the cost of information rent paid to high-type sellers, the monopoly platform increases fees for low-type sellers.

5. Conclusion

The network effect has been a dominant theme within platform ecosystem research. However, the crucial role of congestion in platform dynamics has received less attention in the existing literature. While a growing seller base traditionally translates to increased user utility, user experience is not guaranteed to improve monotonically with a growing seller base (Poddar and Banerjee 2024; Sokullu 2023). Specifically, a larger seller base can lead to delay-related negative experiences for consumers, a factor often overlooked in current research. Our work addresses this gap by being the first to incorporate the combined effects of cross-side congestion on buyers and information asymmetry within the two-sided marketplace. By developing a model that integrates these critical issues, we aim to provide a deeper understanding of how information asymmetry interacts with cross-side congestion effects within platform markets.

To address this critical gap in the literature, we propose a two-part model investigating a monopoly platform with two user groups: buyers and sellers. Buyers benefit from cross-side network effects but experience congestion effects (decreased utility with more sellers due to delays). We establish a benchmark model assuming the platform has perfect information about seller types. This allows us to analyze the platform's fee structure and user behavior in a baseline scenario where information asymmetry is absent. We then extend the model to incorporate asymmetric information. Here, the platform lacks complete knowledge about the marginal gain sellers receive by supplying per-unit of quality. We further explore two cases of network effects within each setting: Positive network benefits outweigh congestion effects, and Congestion effects outweigh positive network benefits. By analyzing these different regimes and cases, we aim to derive market equilibrium conditions and identify how the interplay of information asymmetry, network effects, and congestion shapes platform dynamics.

Our comparative analysis reveals distinct platform fee structures depending on whether the platform has complete information about sellers (perfect information) or not (asymmetric information). In both regimes, when congestion outweighs positive network effects, the platform charges a positive fee to sellers (especially low-type sellers in the asymmetric case) to manage congestion. Conversely, when positive network effects are stronger, the platform incentivizes participation by charging no fees under symmetric information regime. Interestingly, under asymmetric information, high-type sellers benefit from a lower revenue-sharing fee compared to the perfect information scenario, while low-type sellers pay a higher fee. To further explore these dynamics, we conducted a sensitivity analysis examining how the relative strengths of network and congestion effects influence platform fees.

The study has a few limitations. Firstly, we focus on cross one-sided congestion, where congestion arises from sellers to buyers. Incorporating same-side congestion among buyers could be an interesting extension of this research. Secondly, we do not explicitly model seller competition. Finally, we abstract from platform competition. These aspects represent potential avenues for future research.

Data availability The data that support the findings of this study are available from the corresponding author upon request.

Declaration of competing interest The authors declare no conflict of interest.

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Appendix: Proofs and Computations

A. Decision of Monopoly platform on optimal fees under symmetrical information case

$$\Pi_P = \frac{1}{2}(p_h^B D_h + \alpha_h \Phi^h q_h N_h^S) + \frac{1}{2}(p_l^B D_l + \alpha_l \Phi^l q_l N_l^S)$$

$$= \frac{1}{2}\left[\frac{p_h^B}{(\overline{\theta}-\underline{\theta})}\left[\overline{\theta} - \frac{\{(p_h^B-p_l^B)-(s_h-s_l)\}\ \beta}{\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}}\right] + \frac{p_l^B}{(\overline{\theta}-\underline{\theta})}\left[\frac{\{(p_h^B-p_l^B)-(s_h-s_l)\}\beta}{\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}} - \frac{\{p_l^B-s_l-\Psi(N_s)\}\ \beta}{(1-\alpha_l)\phi^l}\right] + \frac{\alpha_h}{K_h}\left[\frac{(1-\alpha_h)^3\phi^{h^4}}{2\beta^2}\right] + \frac{\alpha_l}{K_l}\left[\frac{(1-\alpha_l)^3\phi^{l^4}}{2\beta^2}\right]\right] \quad \text{(A1)}$$

$$\frac{\partial \Pi_P}{\partial p_h^B} = \frac{1}{(\overline{\theta}-\underline{\theta})}\left[\left\{\overline{\theta} - \frac{\{(p_h^B-p_l^B)-(s_h-s_l)\}\ \beta}{\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}} - \frac{p_h^B\beta}{\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}}\right\} + \frac{p_l^B\beta}{\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}}\right] = 0$$

$$\text{Or, } p_h^B = p_l^B + \frac{\overline{\theta}}{2\beta}\{(1-\alpha_h)\phi^h - (1-\alpha_l)\phi^l\} + \frac{(s_h-s_l)}{2} \quad \text{(A2)}$$

$$\frac{\partial \Pi_P}{\partial p_l^B} = \frac{1}{(\overline{\theta}-\underline{\theta})}\left[\frac{p_h^B\beta}{\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}} + \frac{\{(p_h^B-p_l^B)-(s_h-s_l)\}\beta}{\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}} - \frac{\{p_l^B-s_l-\Psi(N_s)\}\ \beta}{(1-\alpha_l)\phi^l} - p_l^B\beta\left\{\frac{1}{\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}} + \frac{1}{\{(1-\alpha_l)\phi^l\}}\right\}\right] = 0$$

$$\text{Or, } p_l^{B*} = \frac{\overline{\theta}(1-\alpha_l)\phi^l}{2\beta} + \frac{1}{2}[s_l + \Psi(N_S)] \quad \text{(A3)}$$

From (A2), we obtain,

$$p_h^{B*} = \frac{\overline{\theta}(1-\alpha_h)\phi^h}{2\beta} + \frac{1}{2}[s_h + \Psi(N_S)] \quad \text{(A4)}$$

Substituting p_l^B and p_h^B from equations (A3) and (A4) respectively in equation (A1), we obtain,

$$\Pi_P = \frac{1}{2}\left[\frac{1}{(\overline{\theta}-\underline{\theta})}\left[\frac{\overline{\theta}(1-\alpha_h)\phi^h}{2\beta} + \frac{1}{2}\{s_h + \Psi(N_S)\}\right]\left[\frac{\overline{\theta}}{2} + \frac{(s_h-s_l)\beta}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}}\right] + \frac{1}{(\overline{\theta}-\underline{\theta})}\left[\frac{\overline{\theta}(1-\alpha_l)\phi^l}{2\beta} + \frac{1}{2}\{s_l + \right.\right.$$

$$\left.\left.\Psi(N_S)\}\right]\left[\frac{\beta}{2}\frac{\{s_l+\Psi(N_S)\}}{(1-\alpha_l)\phi^l} - \frac{(s_h-s_l)\beta}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}}\right] + \frac{\alpha_h}{K_h}\left[\frac{(1-\alpha_h)^3\phi^{h^4}}{2\beta^2}\right] + \frac{\alpha_l}{K_l}\left[\frac{(1-\alpha_l)^3\phi^{l^4}}{2\beta^2}\right]\right]$$

Differentiating with respect to α_h and α_l, we obtain,

$$\frac{\partial \Pi_P}{\partial \alpha_h} = \frac{1}{(\overline{\theta}-\underline{\theta})}\left[\left[-\frac{\overline{\theta}\phi^h}{2\beta} + \frac{1}{2}\frac{\partial\Psi(N_S)}{\partial\alpha_h}\right]\left[\frac{\overline{\theta}}{2} + \frac{(s_h-s_l)\beta}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}}\right] + \frac{(s_h-s_l)\beta\phi^h}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}^2}\left[\frac{\overline{\theta}(1-\alpha_h)\phi^h}{2\beta} + \frac{1}{2}\{s_h + \Psi(N_S)\}\right] + \right.$$

$$\left[\frac{1}{2}\frac{\partial\Psi(N_S)}{\partial\alpha_h}\right]\left[\frac{\beta}{2}\frac{\{s_l+\Psi(N_S)\}}{(1-\alpha_l)\phi^l} - \frac{(s_h-s_l)\beta}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}}\right] + \left[\frac{\overline{\theta}(1-\alpha_l)\phi^l}{2\beta} + \frac{1}{2}\{s_l + \Psi(N_S)\}\right]\left[\frac{\beta}{2}\frac{\frac{\partial\Psi(N_S)}{\partial\alpha_h}}{(1-\alpha_l)\phi^l} - \right.$$

$$\left.\left.\frac{(s_h-s_l)\beta\phi^h}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}^2}\right]\right] + \frac{1}{K_h}\left[\frac{(1-\alpha_h)^3\phi^{h^4}}{2\beta^2}\right] - \frac{\alpha_h}{K_h}\left[\frac{3(1-\alpha_h)^2\phi^{h^4}}{2\beta^2}\right] \quad \text{(A5)}$$

$$\frac{\partial \Pi_P}{\partial \alpha_l} = \frac{1}{(\overline{\theta}-\underline{\theta})}\left[\left[\frac{1}{2}\frac{\partial\Psi(N_S)}{\partial\alpha_l}\right]\left[\frac{\overline{\theta}}{2} + \frac{(s_h-s_l)\beta}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}}\right] - \left[\frac{\overline{\theta}(1-\alpha_h)\phi^h}{2\beta} + \frac{1}{2}\{s_h + \Psi(N_S)\}\right]\frac{(s_h-s_l)\beta\phi^l}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}^2} + \right.$$

$$\left[-\frac{\overline{\theta}\phi^l}{2\beta} + \frac{1}{2}\frac{\partial\Psi(N_S)}{\partial\alpha_l}\right]\left[\frac{\beta}{2}\frac{\{s_l+\Psi(N_S)\}}{(1-\alpha_l)\phi^l} - \frac{(s_h-s_l)\beta}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}}\right] + \left[\frac{\overline{\theta}(1-\alpha_l)\phi^l}{2\beta} + \frac{1}{2}\{s_l + \Psi(N_S)\}\right]\left[\frac{\beta}{2}\frac{\frac{\partial\Psi(N_S)}{\partial\alpha_l}}{(1-\alpha_l)\phi^l} + \frac{\beta}{2}\frac{\{s_l+\Psi(N_S)\}}{(1-\alpha_l)^2\phi^l} + \right.$$

$$\left.\left.\frac{(s_h-s_l)\beta\phi^l}{2\{(1-\alpha_h)\phi^h-(1-\alpha_l)\phi^l\}^2}\right]\right] + \frac{1}{K_l}\left[\frac{(1-\alpha_l)^3\phi^{l^4}}{2\beta^2}\right] - \frac{\alpha_l}{K_l}\left[\frac{3(1-\alpha_l)^2\phi^{l^4}}{2\beta^2}\right] \quad \text{(A6)}$$

Case I ($0 \leq \mathbf{N_s} \leq \widehat{\mathbf{N_s}}$): For this zone, we observe $\frac{\partial\, \Psi(\mathrm{N_S})}{\partial \alpha_\mathrm{l}} < 0$; $\frac{\partial\, \Psi(\mathrm{N_S})}{\partial \alpha_\mathrm{h}} < 0$. Therefore we obtain, $\frac{\partial \Pi_P}{\partial \alpha_l} < 0$; $\frac{\partial \Pi_P}{\partial \alpha_h} < 0$. For the rising portion of the externality curve we derive corner solution as ${\alpha_{l1}}^* = 0$ and ${\alpha_{h1}}^* = 0$.

Case II ($\widehat{\mathbf{N_s}} < \mathbf{N_s} \leq \overline{\mathbf{N_s}}$)**:** For the falling range of the externality curve, we obtain, $\frac{\partial \Pi_P}{\partial \alpha_l} = 0$ and $\frac{\partial \Pi_P}{\partial \alpha_h} = 0$. Thus, we derive (interior) solution for fees as $({\alpha_{h2}}^*, {\alpha_{l2}}^*)$.