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Decision Analysis

Analysis of mutual benefit from information sharing and exchange between an online platform and a seller

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ABSTRACT

When a seller uses both a direct sales channel and an external online platform, the seller and the platform can obtain private yet correlated *market signals* that improve demand forecasting. This setting motivates an analysis of *whether, and under what conditions*, they should *unilaterally* share or *mutually* exchange these signals. While the platform sets its commission rate and the seller determines its selling price, we investigate whether *bilateral* "exchange" can address the incentive misalignment inherent in *unilateral* "sharing," thereby enabling both parties to maximize their profits by leveraging each other's signals. Our equilibrium analysis reveals that when demand for the seller's online channel is sufficiently high, the seller can incentivize the platform to unilaterally share its signal via a side payment. Furthermore, when the seller's signal is highly precise, unilateral sharing can benefit both parties, regardless of the relative market sizes of the two channels. However, mutual exchange yields no additional benefit over unilateral sharing for either party. Even when the commission rate is fixed and independent of signals, the platform can still achieve a win-win outcome through unilateral sharing by using a two-part tariff, albeit with a higher commission than in the no-sharing scenario.

1. Introduction

To expand market reach, brands (sellers) such as Adidas and Under Armour often sell their products through their own "direct" channels (i.e., online and offline stores) as well as external online sales "platforms" such as Amazon. As a result, different channels observe private and yet correlated "market signals" such as consumer preference trends (Hübner et al., 2022). Although both the seller and the platform observe market signals from different sources, neither party possesses complete information about the market. As a result, each party holds valuable but private information that could help the other party make better decisions. For instance, sellers can benefit from receiving information from the platform to better set prices across their channels. Conversely, platforms can gain from obtaining market information from sellers, enabling them to set optimal commission rates.

The platform's sales commission rate is typically fixed in advance before the seller sets its price. For example, Temu charges a commission rate ranging from 5% to 20% per order, depending on the product category, for sales facilitated through its platform (Temu, 2025). In such cases, when the platform's commission rate is predefined, sharing private information about market uncertainty can help sellers make more informed pricing decisions. Since an increase in seller sales enhances the platform's commission-based revenue, platforms are often willing to voluntarily share their market signals with sellers (Zhang & Zhang, 2020). Amazon, for instance, offers the Product Opportunity Explorer program, which provides sellers with information such as customer behavior, product catalog insights, and anonymized sales data at no cost (Amazon, 2023a). This prevalence of unilateral information sharing stems from the pre-announcement of fixed commission rates, fostering a symbiotic relationship between platforms and sellers.

Instead of fixed commission rates, we observed that online platforms have begun adjusting their commission rates more frequently, as seen in Amazon's referral fees (Amazon, 2023b). To set appropriate commission rates, platforms should incorporate the market insights held by sellers. Since platforms might offer tiered commission rate structures where greater demand can lead to reduced commission rates, the seller's market signal becomes essential for designing such structures. For instance, TikTok Shop, as a pure agent/marketplace, increased its commission rate from 5% to 9% as the marketplace grew. Such updates can occur frequently, driven by the platform's understanding

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of sellers' economics, including market size, growth, and profit margin. Moreover, TikTok conditionally lowers its commission rate for new sellers if they provide their full product catalog information to the marketplace within 45 days of onboarding, allowing the platform to gather seller-specific information through this offer (TikTok, 2023). Furthermore, Zalando SE nowadays charges commission rates based on sellers' selling prices in its marketplace (Zalando, 2023). As a result, platforms have an incentive to understand how sellers determine their prices, which are directly associated with sellers' private signals, rather than committing to fixed commission rates.

These observations suggest that, in practice, both the seller and the platform have economic incentives to learn from each other's private signals. While a platform's information revelation under a revenue-sharing contract has been widely studied, the impact of information sharing under commission rate decisions on the performance of a seller and an online platform remains unclear (Hyndman et al., 2013; Mishra et al., 2009; Zhang & Chen, 2013). Moreover, the effect of mutual information exchange on both parties' expected profits has been rarely investigated. These observations motivate us to examine *whether, and under what conditions,* the two parties "share" or "exchange" their private market signals. To address this research gap, we pose the following research questions: (1) When the commission rate decision is endogenized, can the platform's unilateral sharing still be mutually beneficial? (2) Is there any incentive for the seller to share her market signal unilaterally to induce the platform to set a lower commission rate? (3) Would exchanging both signals between the platform and the seller be mutually beneficial?

Our equilibrium analysis offers several managerial insights. First, sellers are willing to compensate platforms to encourage information sharing—especially when the bulk of their revenue is generated through the platform. Second, when a seller holds more precise information about general market uncertainty and maintains a strong direct sales channel, unilateral information sharing by the seller can lead to a win-win outcome. By sharing, the platform can reduce demand variability and fully observe the seller's price reaction function, enabling it to lower its commission rate. Third, in environments where unilateral sharing is available, mutual information exchange may be suboptimal. The platform benefits more when the seller shares information unilaterally, as it can leverage the inference effect through its announced commission rate. Conversely, when the platform shares its information unilaterally, the seller enjoys higher expected profits than under mutual exchange, since the platform cannot fully observe her pricing strategy. Thus, mutual exchange is not always preferred by both parties. Finally, if the platform sets its commission rate before acquiring private information about market uncertainty, it can charge a premium for sharing its insights with the seller—resulting in a mutually beneficial outcome.

The remainder of this paper is structured as follows: In Section 2, we provide an overview of the relevant literature. Model formulations are presented in Section 3. The equilibrium analysis and managerial insights derived from the model with bilateral information exchange are discussed in Section 4. Section 5 presents the equilibrium analysis and implications with unilateral information sharing. Section 6 compares the equilibrium results between information sharing and exchange. Section 7 extends the model by considering the platform's commission rate as a long-term decision made prior to the realization of private information. Lastly, Section 8 provides concluding remarks and outlines avenues for future research. The appendix contains all the proofs.

2. Literature review

Our paper is related to three research streams: (1) market information sharing under platform business, (2) information exchange in supply chains, and (3) platform retailing as a common marketplace.

Market Information Sharing under Platform Business: Zhang and Zhang (2020) investigate an e-tailer's incentive to share demand information with suppliers who can use such information to expand their offline channel. They show that if the e-tailer is a selling agency, it shares the information with the supplier if the offline setup cost is relatively low or high. On the other hand, under high accuracy of demand information, the e-tailer remains silent to avoid channel competition. Tsunoda and Zennyo (2021) explore a platform's optimal demand information-sharing policy with a supplier, where the platform competes with an offline retailer selling an identical product from the same supplier. The platform charges a commission rate while the supplier sets a wholesale price. They examine the impact of the platform's information sharing on the supplier's optimal channel decision and show that sharing enables Pareto improvement for the supplier, the retailer, and the platform.

Li et al. (2021) investigate a platform's optimal demand information sharing decision where the platform can share either with a manufacturer, a reseller, or both. While the reseller orders from the manufacturer under a wholesale price-only contract, they both sell the products via a common platform. They show that if demand is highly uncertain and competition is intense, the platform shares demand information only with the manufacturer. This is because double marginalization can be mitigated by a signaling effect that makes the reseller infer the information from the manufacturer's pricing decisions and eventually reduces her price. Liu et al. (2021) investigate a platform's optimal sharing decision with multiple sellers under Cournot competition. Their results show that sharing demand information is always an equilibrium strategy. The platform shares information truthfully if it can selectively share part of its information with certain sellers. Zhong et al. (2023) consider a platform that decides whether to share demand information with a manufacturer and a retailer (seller). They compare optimal sharing decisions under two settings: (1) the platform with encroachment and (2) the platform without encroachment. They demonstrate that the platform, as a reseller, always has an incentive to share its information with the seller but not with the manufacturer.

Tang et al. (2023) examine a platform's decision to share demand information with a supplier who is considering encroaching through either an agency model (selling via the platform) or a direct model (opening independent stores). They find that when the supplier chooses the mode of encroachment before the platform decides whether to share information, the platform strategically shares demand information to encourage agency encroachment. Gong et al. (2024) study how a manufacturer's decision between reselling and agency formats is affected by the platform's demand information-sharing policy. They show that when perceived information accuracy is low, the manufacturer opts for the agency model at low commission rates and switches to reselling at high commission rates, while the platform chooses not to share information. Additionally, the value of information sharing increases as the perceived accuracy improves from moderate to high levels.

Information Exchange in Supply Chains: Yue and Liu (2006) consider a manufacturer who offers its product both via its direct sales channel and to a retailer. Both parties have private demand information and can vertically exchange their information. The information exchange decision is made ex-ante before they set wholesale and selling prices, respectively. They show that the information exchange always benefits the manufacturer. However, the retailer benefits only if the manufacturer expects the retailer's forecast to be higher than the actual forecast of the retailer. Gal-Or et al. (2008) study demand information exchange in a vertical supply chain. They examine different characteristics of demand information possessed by a manufacturer and two competing retailers. While the retailers have more accurate sales data, the manufacturer has a better overview of demand correlations among different markets. They demonstrate that as the retailers can infer the manufacturer's demand information through his wholesale price, without information exchange, the manufacturer sets a lower price. They find that although information exchange benefits the manufacturer, he exchanges only with the retailer endowed with a noisier signal if exchanging information incurs costs.

Li and Zhang (2008) consider information exchange decisions among competing retailers and a manufacturer. Each retailer possesses its own demand signal and decides whether to reveal the information vertically to the manufacturer or not. Once the information decision is made by the retailers, the manufacturer can either keep it confidential or disclose it to the other retailers. They show that when confidentiality is ensured and price competition intensity is high among the retailers, they share private information. However, under confidentiality, the manufacturer ends up lowering the wholesale price as the retailers infer the others' information through the manufacturer's wholesale price, leading to a signaling effect. Dai et al. (2022) consider a manufacturer and a retailer where the manufacturer has a dual-channel strategy. While both parties can decide whether to reveal their private demand information to each other vertically, they demonstrate that the mutual exchange only benefits the manufacturer when the competition between the channels is low.

Platform Retailing as a Common Marketplace: Conventionally, there are two selling models of a platform as an online marketplace: (1) agency model and (2) reselling model. In the first format, the platform only offers a common marketplace as an e-tailer and charges a commission rate to manufacturers (sellers) using a revenue-sharing scheme. In the reselling model, the platform buys products from the manufacturers directly and sets selling prices to its customers. Abhishek et al. (2016) show that if the platform is an agent, the selling prices of manufacturers are lower than when the platform is a reseller. Further, they demonstrate that if offering the platform's online channel reduces the manufacturers' direct channel demands, the platform prefers to be an agency. Wang et al. (2019) propose a "cost-sharing joint commission" contract mechanism to overcome efficiency loss from a decentralized supply chain between a manufacturer and a platform. While the platform is the leader and decides a commission rate to charge to the manufacturer first, they investigate the impact of fairness concerns (i.e., the fairness of the income distribution between a giant e-commerce platform and a manufacturer) on the manufacturer's equilibrium selling price and the platform's commission rate decisions. Zennyo (2020) considers two competing suppliers with different market sizes and a monopolistic platform. Both suppliers can opt for either wholesale price or agency contracts when using a platform's common marketplace, while the platform decides on an optimal commission rate. He demonstrates that when substitutability between the suppliers' products is low, the platform sets a lower commission rate to induce the suppliers to prefer the agency contract over the wholesale price contract.

Hasiloglu and Kaya (2021) consider two sellers using a common online platform. While the online platform sets a commission rate, and the sellers decide on both service level and selling prices, they state that when competition is high between the sellers, the platform's commission rate increases. Tsunoda and Zennyo (2021) examine the impact of the platform's information-sharing decision on a supplier's channel choice via the platform (i.e., wholesale and agency models). They show that the platform sets a lower commission rate so that the supplier opts for the agency over the wholesale model. Further, sharing information induces the supplier to choose the agency model. Whilst previous works focus on the supplier's choice between either the wholesale or the agency models, Ha et al. (2022) present conditions under which a manufacturer can operate with the platform's dual channel (i.e., agency and reselling channels). They show that introducing the agency model reduces the wholesale price, and the manufacturer's operational flexibility under dual channels makes the platform increase the service effort. Martínez-de-Albéniz et al. (2022) present a dynamic optimal control model and analyze conditions when a supplier joins a platform's common marketplace while the platform sets flexible (via fully dynamic commission rates) or fixed commission rates. They demonstrate that although a flexible commission rate is more efficient, in general, when the supplier decides on inventory contingent on the platform's commission rate offer, a fixed (static) commission rate brings a higher long-term profit.

Research Gaps and Contributions: First, the existing literature extensively examines the advantages of online platforms engaging in unilateral information sharing. Although mutual information exchange has been studied, it has primarily focused on the relationship between a supplier and a retailer. To address this gap, our analysis explores the scenario in which a seller and an online platform can either unilaterally share or mutually exchange private information. Moreover, existing literature on platform retailing has mainly focused on how the platform's commission rate decision influences the choice of channel formats, such as wholesale and agency models. However, there is limited understanding of how the seller's information sharing impacts the platform's commission rate decision. This aspect is particularly important given the recent trend among large platforms to frequently optimize their commission rates based on product categories and regions. The market signals from individual sellers could, therefore, be invaluable in determining the platform's optimal commission rates. Thus, we investigate the conditions under which the platform and the seller benefit from unilateral sharing or bilateral exchange of each other's market information.

3. Model assumptions

Consider a seller of a single product with two separate channels: (1) a direct sales channel controlled by the seller and (2) an external online platform. The platform determines a commission rate r as a percentage of the seller's revenue generated via the online platform. Without loss of generality, assume that marginal costs for both the platform and the seller are zero (Huang et al., 2018; Zha et al., 2023). Given the commission rate r, the seller sets an optimal price p. Based on the evidence that multichannel sellers often offer identical prices across channels to avoid arbitrage or confusion, we assume that channel-specific selling prices are not permissible. Empirical studies have shown that, for products such as electronic devices and clothing, prices tend to be identical between online and direct sales channels; hence, price differences between online and offline channels should not be a significant concern (Cavallo, 2017).

Demand Functions q_O and q_D. The demands generated from the two separate online and direct sales channels are assumed to be linearly dependent on the selling price p:

$$q_O = a_O + m - b_O \cdot p \quad \text{and} \quad q_D = a_D + m - b_D \cdot p, \tag{1}$$

where a_O and a_D represent the "market potential" of the online and direct sales channels, respectively. Although the selling price is the same in both channels, the consumers using each channel can vary, leading to different price-dependent demand rate coefficients denoted by b_O and b_D.

Market Uncertainty m. From (1), we assume that a_O, a_D, b_O, and b_D are common knowledge; however, customer demands q_O and q_D are subject to "market uncertainty" m, which represents an adjustment to the market potentials a_O and a_D due to uncertain macroeconomic factors affecting the seller's product and/or market conditions. For example, market uncertainty may arise from factors such as inflation, geopolitical events, global trade tariff policies, fiscal policies, and disruptive technologies that gradually shift general consumer preferences over time. Consequently, both the online and direct sales channels are subject to the same market uncertainty m, as these economic conditions and sources of randomness affect overall market dynamics irrespective of the channel. This assumes perfectly correlated channel-specific randomness, i.e., $m = m_D = m_O$. Although it is possible to assume channel-specific market uncertainty, as long as there is a positive correlation between the market uncertainties (i.e., $0 < \rho(m_D, m_O) < 1$), the incentive for information sharing persists (Gal-Or et al., 2008). Therefore, for simplicity, we focus on the case of perfect correlation. For tractability, we assume that $m \sim N(0,\sigma)$ and denote $\nu \equiv \frac{1}{\sigma}$ as "market certainty". To avoid trivial cases, a_O and a_D are assumed to be sufficiently large, and the variance of the market uncertainty σ is reasonably bounded such that the seller's price p and the platform's commission rate r are ensured to be positive with high probability (Chen & Tang, 2015; Ha et al., 2011; Li, 2002).

Noisy Signals x_S and x_P. The demands q_O and q_D given in (1) are influenced by market uncertainty m, which may hinder the seller and the platform from making optimal pricing decisions p and commission rate decisions r, respectively. Therefore, capturing more information about market uncertainty m to better forecast demands can benefit both parties. Both the seller and the platform obtain private and noisy signals about m through different sources, and the private information possessed by one party can benefit the other. Since each party has access to distinct sources of information, the seller and the platform obtain "noisy and imperfect" private and yet correlated signals about the uncertain market m. The seller observes her private and noisy signal x_S about market uncertainty m by conducting consumer surveys and market analysis. Meanwhile, the platform leverages its direct observations of online consumer behavior — such as browsing history, click sequences, and purchasing patterns — to deduce its private and noisy signal x_P about m. Following Grossman (1981) and Mendelson and Tunca (2007), the noisy signals obtained by the seller and the platform satisfy:

$$x_S = m + \varepsilon_S, \quad \text{and} \quad x_P = m + \varepsilon_P. \tag{2}$$

For tractability, we assume that the noise in the signals follows $\varepsilon_S \sim N(0,\tau_S)$ for the seller and $\varepsilon_P \sim N(0,\tau_P)$ for the platform. τ_S and τ_P are common knowledge, meaning they are known by both players. The noise is characterized by the variance τ_S for the seller and τ_P for the platform. To simplify the interpretation of results later, we define $\nu_S \equiv \frac{1}{\tau_S}$ and $\nu_P \equiv \frac{1}{\tau_P}$ as the "precision" of the private signals. For instance, $\nu_S \to 0$ can be interpreted as the case where the seller cannot obtain her own private signal, while $\nu_S \to \infty$ corresponds to the case where the seller's private signal is perfect. For ease of exposition, we assume that the noise terms ε_S and ε_P are independent of the market uncertainty m and of each other, with $\text{cov}(m,\varepsilon_S) = \text{cov}(m,\varepsilon_P) = \text{cov}(\varepsilon_P,\varepsilon_S) = 0$. However, note that the private signals x_S and x_P are "correlated" with the market uncertainty m in an additive form. As a result, the signals x_S and x_P serve as unbiased estimators of the market uncertainty m. Moreover, the seller's signal x_S and the platform's signal x_P are positively correlated as $Corr(x_S,x_P) = \frac{1}{\sqrt{1+\frac{\nu}{\nu_S}}\sqrt{1+\frac{\nu}{\nu_P}}} > 0$.

Structure of Analysis. The structure of our analysis is illustrated in Table 1. For each setting, we analyze the equilibrium price of the seller, p, the equilibrium commission rate of the platform, r, the ex-ante expected profit for the seller, Π_S, and the ex-ante expected profit for the platform, Π_P, under four scenarios: (1) No information exchange (N); (2) With mutual information exchange (W); (3) Platform's unilateral information sharing (PI), where the platform provides x_P to the seller; (4) Seller's unilateral information sharing (SI), where the seller provides x_S to the platform.

In the case of no information exchange (N), as the platform announces the commission rate r based on its private signal, x_P, the seller sets the price after the announcement. In doing so, the seller can infer the platform's private signal as $\hat{x}_P$ from the announced commission rate r. Consequently, we consider the seller's inference effect, which could be harmful to the platform under a no information-revelation scenario. This, in turn, might incentivize the platform to reveal its information to prevent the seller from inferring the signal. Secondly, we derive the equilibrium price and commission rate under mutual information exchange (W), followed by an analysis of the unilateral sharing cases. As unilateral sharing represents a simplified or partial version of mutual exchange, we begin with the more complex mutual exchange scenario to avoid redundant derivations.

While mutual exchange may offer greater benefits, it is only valuable when incentives cannot be aligned through unilateral sharing. Therefore, Section 5 further explores each party's unilateral information sharing. In the absence of information sharing from the seller (SI), the platform cannot infer the seller's private information, as the price decision is made after the commission rate decision. Hence, the seller might be incentivized to actively share her information with the platform upfront, enabling the platform to set a lower commission rate. However, such sharing carries a risk: the seller not only informs the platform of her price reaction function associated with her signal x_S, but also helps it reduce the variance of market uncertainty and extract more revenue from her sharing.

Similarly, regarding the platform's information sharing (PI), the platform earns a commission based on the seller's revenue generated through the online channel. If the seller's inference based on the signal hinders the platform from setting an optimal commission rate, the platform may have an incentive to share its private signal x_P unilaterally. The platform's information disclosure may prevent the seller from forming incorrect beliefs about the market signal; however, it also leads to changes in the platform's own commission rate decision upon sharing. Hence, the seller's benefit from receiving additional information from the platform may not be fully compensated by the increase in the commission rate. We expound the conditions under which this unilateral information sharing can be mutually beneficial. Furthermore, when information is shared or exchanged, the seller and the platform use automated data transfer, which makes it difficult to falsify the data. Therefore, consistent with the existing literature (Shang et al., 2016; Zha et al., 2023), we assume that both parties truthfully share or exchange their private signals.

Sequence of Events. Information sharing or exchange is a long-term decision that requires appropriate investment in information technology infrastructure. However, decisions on price and commission rates are made after market conditions are observed, either directly or through information sharing/exchange. For instance, launching a new or seasonal product in the fashion industry often requires additional market research to address market uncertainty, identify customer trends, and gather competitors' information before setting prices (McKinsey, 2022). Similarly, platforms regularly adjust commission rates based on anticipated market sizes and the growth rates of their sellers, using insights from private signals (Amazon, 2023b; TikTok, 2023). As a result, the platform and the seller commit to information sharing or exchange decisions before observing private signals. Furthermore, as noted by Abhishek et al. (2016) and Tsunoda and Zennyo (2021), platforms that serve as common marketplaces are endowed with substantial power to set commission rates first because online marketplaces have broader customer bases and competing sellers' information.

Using a game-theoretic framework, the sequence of events is as follows: (1) Given four distinct information sharing/exchange structures (see Table 1), signals are realized and shared/exchanged accordingly; (2) The platform determines the commission rate charged to the seller; and (3) The seller sets the selling price for both sales channels. In some cases, however, platforms announce their commission rates early (even before sellers join their common marketplaces). To address this, as an extension presented in Section 7, we consider the case in which the platform commits to its commission rate in advance — prior to any information-sharing decisions — and fixes this rate at the outset of the sequence.

Information Sharing and Exchange. Without information exchange, the seller observes only x_S, and the platform observes only x_P. However, with information exchange, both the seller and the platform observe both signals (x_S, x_P), allowing them to obtain a more accurate forecast of m through variance reduction, as shown in Lemma 1.

Lemma 1. *Without information exchange, each player can determine the conditional expectation and variance of market uncertainty* $(m|x_S)$ *and*

Table 1
Structure of analysis.

	Analysis in Section 4		Analysis in Section 5	
	No exchange (N)	With exchange (W)	Platform's unilateral share (PI)	Seller's unilateral share (SI)
Platform	r^N, Π_P^N	r^W, Π_P^W	r^{PI}, Π_P^{PI}	r^{SI}, Π_P^{SI}
Seller	p^N, Π_S^N	p^W, Π_S^W	p^{PI}, Π_S^{PI}	p^{SI}, Π_S^{SI}

$(m|x_P)$ using $\sigma = \frac{1}{v}$, $\tau_S = \frac{1}{v_S}$, and $\tau_P = \frac{1}{v_P}$, where:

$$\mathbb{E}(m|x_S) = \frac{\sigma}{\sigma+\tau_S}x_S = \frac{v_S}{v+v_S}x_S \quad \text{and} \quad Var(m|x_S) = \frac{\sigma\tau_S}{\sigma+\tau_S} = \frac{1}{v+v_S}$$

$$\mathbb{E}(m|x_P) = \frac{\sigma}{\sigma+\tau_P}x_P = \frac{v_P}{v+v_P}x_P \quad \text{and} \quad Var(m|x_P) = \frac{\sigma\tau_P}{\sigma+\tau_P} = \frac{1}{v+v_P}$$

With information exchange, both the seller and the platform possess the same signals (x_S, x_P), so the conditional expectation and variance of market uncertainty $(m|x_S, x_P)$ are:

$$\mathbb{E}(m|x_S, x_P) = \frac{\sigma\left[\tau_P x_S + \tau_S x_P\right]}{\sigma\tau_P + \sigma\tau_S + \tau_P\tau_S} = \frac{v_S x_S + v_P x_P}{v+v_S+v_P} \quad \text{and}$$

$$Var(m|x_S, x_P) = \frac{\sigma\tau_P\tau_S}{\sigma\tau_P + \sigma\tau_S + \tau_P\tau_S} = \frac{1}{v+v_S+v_P}.$$

Lemma 1 shows that, for any imperfect private signal with $\tau_j > 0$ for $j \in (S, P)$, information exchange enables both parties to improve their forecast accuracy about market conditions through variance reduction, i.e., $Var(m|x_P, x_S) < Var(m|x_S)$ and $Var(m|x_P, x_S) < Var(m|x_P)$. However, it remains unclear how this reduced variance affects the seller's price decision p and the commission rate r. Further, when unilateral information sharing occurs from the platform to the seller under PI, the seller has access to both $\mathbb{E}(m|x_S, x_P)$ and $Var(m|x_S, x_P)$, while the platform only knows its own signal x_P (e.g., $\mathbb{E}(m|x_P)$ and $Var(m|x_P)$). In contrast, when the seller unilaterally shares information under SI, the platform now has access to both $\mathbb{E}(m|x_S, x_P)$ and $Var(m|x_S, x_P)$, while the seller only has her own signal x_S and infers the platform's signal from the announced commission rate r.

4. Mutual information exchange scenarios

4.1. No information exchange (N)

When no information exchange takes place, the platform uses its private signal x_P to set r, and the seller sets p based on the announced commission rate r and her private signal x_S. Following conventional backward induction, equilibrium decisions can be obtained by solving: (i) Given r and x_S, the seller sets $p(r, x_S)$, and (ii) Anticipating the price reaction function $p(r, x_S)$ from (i) with his expectation of the seller's signal $\mathbb{E}[x_S \mid x_P]$, the platform sets its commission rate $r(x_P, \mathbb{E}[p(r, x_S) \mid x_P])$ based on its signal x_P and the anticipated price $p(r, x_S)$. However, a rational seller knows that the platform sets an optimal equilibrium commission rate according to (ii). Hence, the r announced by the platform reflects its private market signal x_P, and the seller sets p using both her own signal x_S and the inferred platform's signal $\hat{x}_P$ derived from r. Therefore, we apply the concept of "*Rational Expectation Equilibrium* (REE)[1]" (e.g., Tang et al., 2024) to characterize how the retailer infers $\hat{x}_P$ based on the revealed information r:

1. Suppose there exists a *rational* equilibrium r^N. Then, the seller infers the platform's signal $\hat{x}_P$ from the platform's announced commission rate r^N, and sets an optimal price $p(r^N, x_S, \hat{x}_P)$ based on r^N, x_S, and the inferred $\hat{x}_P$ via r^N.
2. Anticipating $p(r^N, x_S, \hat{x}_P)$, the platform sets its commission rate $r(x_P, \mathbb{E}[p(r^N, x_S, \hat{x}_P) \mid x_P])$.
3. The platform's optimal commission rate satisfies $r^N = r(x_P, \mathbb{E}[p(r^N, x_S, \hat{x}_P) \mid x_P])$ in *rational expectation equilibrium*, incorporating the seller's inference effect.

We begin by determining the seller's expected profit, the optimal price, and the platform's optimal commission rate, along with its expected profit. Additionally, we demonstrate that the seller can infer $\hat{x}_P$ based on the given commission rate, $r^N(x_P)$ by applying the inverse of the platform's optimal commission rate decision rule with respect to x_P, thereby forming a rational belief about x_P in equilibrium through r.

Expected Profit of the Seller with *Inference Effect*. By considering the expected demands from both channels q_O and q_D, from (1), along with the given commission rate r and price p, the seller's total expected profit derived from both channels, associated with the observed signal x_S and inferred signal $\hat{x}_P$ is:

$$\begin{aligned}\mathbb{E}\left(\pi_S^N \mid p; x_S, r, \hat{x}_P\right) &= \underbrace{p(1-r)\cdot\mathbb{E}(q_O \mid x_S, \hat{x}_P)}_{\text{Online channel profit}} + \underbrace{p\cdot\mathbb{E}(q_D \mid x_S, \hat{x}_P)}_{\text{Direct channel profit}} \\ &= p(1-r)\cdot\left(a_O + \mathbb{E}\left(m \mid x_S, \hat{x}_P\right) - b_O\cdot p\right) \\ &\quad + p\cdot\left(a_D + \mathbb{E}\left(m \mid x_S, \hat{x}_P\right) - b_D\cdot p\right)\end{aligned} \tag{3}$$

The expected profit function is quadratic in p, and the random variables (m, x_S, and $\hat{x}_P$) follow a multivariate normal distribution, with $m \sim N(0, \sigma)$, $x_S \sim N(0, \tau_S)$ and $\hat{x}_P \sim N(0, \tau_P)$. Hence, we can derive an optimal price p^N for any given x_S and inferred signal $\hat{x}_P$, which exhibits the following linear decision rules: $p^N = A^N + A_S^N\mu_S x_S + A_S^N\mu_P\hat{x}_P$.

Seller's Optimal Price. The optimal price p^N maximizes the seller's expected profit function $\mathbb{E}\left(\pi_S^N \mid p; x_S, r, \hat{x}_P\right)$, based on her observed signal x_S and the inferred signal from the platform $\hat{x}_P$, as given in (3).

Proposition 1. *When there is no information sharing, the seller's optimal price p^N, upon observing her signal x_S and inferring the platform's signal $\hat{x}_P$ via the announced r, satisfies: $p^N = A^N + A_S^N\mu_S x_S + A_S^N\mu_P\hat{x}_P$, where $A^N = \frac{a_O(1-r)+a_D}{2[(1-r)b_O+b_D]}$, $A_S^N = \frac{2-r}{2[(1-r)b_O+b_D]}$, $\mu_S = \frac{v_S}{v+v_S+v_P}$ and $\mu_P = \frac{v_P}{v+v_S+v_P}$.*

We can interpret A^N as the *base price*, which factors in the commission rate r established by the platform in advance, along with the potential market demands from the two channels (a_O and a_D). Additionally, $A_S^N\mu_S$ and $A_S^N\mu_P$ represent the *information factors* associated with the private signal of the seller x_S and the inferred signal $\hat{x}_P$. The comparative statics of the equilibrium price can be summarized as follows:

$$\frac{\partial A^N}{\partial a_O} > 0, \qquad \frac{\partial A^N(A_S^N)}{\partial b_O} < 0, \quad \text{and} \quad \frac{\partial A^N}{\partial r} = \frac{-(a_O b_D - a_D b_O)}{2[(1-r)b_O + b_D]^2},$$

$$\frac{\partial A^N}{\partial a_D} > 0, \qquad \frac{\partial A^N(A_S^N)}{\partial b_D} < 0, \quad \text{and} \quad \frac{\partial A_S^N}{\partial r} = \frac{b_O - b_D}{2[(1-r)b_O + b_D]^2}.$$

From the comparative statics, the seller's equilibrium price p^N increases with a higher commission rate r ($\frac{\partial A^N}{\partial r} > 0$) when the market

[1] In signaling games with continuous types, two prominent equilibrium concepts, Rational Expectations Equilibrium (REE) and Perfect Bayesian Equilibrium (PBE), are commonly used to refine the Nash equilibrium by incorporating beliefs and the information structure. While REE assumes that beliefs are directly determined by the equilibrium mapping, PBE allows for more flexible belief specifications. Additionally, REE often ensures a unique equilibrium by imposing competitive expectations, whereas PBE typically admits multiple equilibria without further refinements literature (Cho & Kreps, 1987; Grossman, 1981; Lucas, 1972). Given our assumption of truthful information sharing, we adopt REE to ensure tractability and uniqueness, thereby avoiding the need for additional refinement mechanisms to select among multiple equilibria.

potential of the online channel is relatively small compared to the direct channel ($\frac{a_O}{a_D} < \frac{b_O}{b_D}$). Conversely, if the online channel's market potential exceeds that of the direct channel ($\frac{a_O}{a_D} \geq \frac{b_O}{b_D}$), a higher commission rate r causes the seller to reduce the equilibrium price p^N ($\frac{\partial A^N}{\partial r} < 0$).

The reason behind such a price decision is that while the platform's commission rate is charged on the online market revenue, the seller offers the same price p^N to both markets (q_O and q_D). In equilibrium, the seller balances the price p^N and the demands in both markets, $q_O = a_O + m - b_O p^N$ and $q_D = a_D + m - b_D p^N$. Therefore, when the commission rate increases, a seller with a smaller online market potential ($\frac{a_O}{a_D} < \frac{b_O}{b_D}$) shifts toward generating the majority of her revenue from the relatively larger direct sales market by raising the selling price. In contrast, when the online market potential is high ($\frac{a_O}{a_D} \geq \frac{b_O}{b_D}$), the seller focuses on extracting most of the revenue from the online market. In this case, as the platform increases its commission rate, the seller lowers the price to attract more demand from the online market.

Expected Revenue of the Platform. We now define the platform's expected revenue based on his private x_P and then derive r^N. While the seller's price p^N from Proposition 1 depends on her private signal x_S and the inferred signal $\hat{x}_P$, the platform does not know the seller's signal x_S without information exchange. Therefore, the platform uses its expectation of the seller's optimal price, which depends on x_S, by using its own signal x_P as $\mathbb{E}(p^N|x_P)$, where $\mathbb{E}\left(p^N \mid x_P\right)$ is expressed as follows:

$$\begin{aligned}\mathbb{E}(p^N|x_P) &= A^N + A_S^N \mu_S \mathbb{E}(x_S \mid x_P) + A_S^N \mu_P \hat{x}_P \\ &= A^N + A_S^N \mu_S \frac{v_P}{v + v_P} x_P + A_S^N \mu_P \hat{x}_P.\end{aligned} \tag{4}$$

The derivation follows from our assumption that $\text{cov}(m, \epsilon_P) = \text{cov}(m, \epsilon_S) = \text{cov}(\epsilon_S, \epsilon_P) = 0$ and $\text{cov}(m, x_P) = \text{cov}(x_P, x_S) = \sigma$. As the conditional expectation of the seller's signal x_S in (4) is derived as $\mathbb{E}(x_S \mid x_P) = \mathbb{E}(m + \epsilon_S \mid x_P) = \mathbb{E}(m \mid x_P)$, we combine this observation with Lemma 1 to obtain (4). The platform's expected revenue $\mathbb{E}(\pi_P^N|r; x_P)$, given its private signal x_P, is:

$$\begin{aligned}\mathbb{E}(\pi_P^N|r; x_P) &= r \cdot \mathbb{E}[p^N q_O \mid x_P] \\ &= r \cdot \mathbb{E}\left[p^N \left(a_O + \frac{v_P}{v + v_P} x_P - b_O p^N\right) \mid x_P\right].\end{aligned} \tag{5}$$

Since the seller infers $\hat{x}_P$ from any given r due to the monotonicity of the commission rate decision r in x_P (as demonstrated later in Lemma 2), the platform recognizes that the seller's inferred signal $\hat{x}_P$ follows a rational belief in equilibrium regarding x_P via r, under no information exchange. The platform then incorporates this seller's reaction function into its optimal commission rate decision.

Platform's Optimal Commission Rate r^N. Considering the platform's revenue $\mathbb{E}(\pi_P^N|r; x_P)$ in (5), the platform's optimal commission rate r^N for any observed private signal x_P maximizes $\mathbb{E}(\pi_P^N|r; x_P)$. By differentiating $\mathbb{E}(\pi_P^N|r; x_P)$ with respect to r, the optimal commission rate r^N is the solution to the following equation:

$$a_O = \underbrace{b_O \frac{\mathbb{E}\left[\left(p^N\right)^2 \mid x_P\right] + r\frac{\partial \mathbb{E}\left[\left(p^N\right)^2 | x_P\right]}{\partial r}}{\mathbb{E}\left[p^N \mid x_P\right] + r\frac{\partial \mathbb{E}\left[p^N | x_P\right]}{\partial r}} - \frac{v_P}{v + v_P} \frac{\mathbb{E}\left[p^N \cdot x_P \mid x_P\right] + r\frac{\partial \mathbb{E}\left[p^N \cdot x_P | x_P\right]}{\partial r}}{\mathbb{E}\left[p^N \mid x_P\right] + r\frac{\partial \mathbb{E}\left[p^N | x_P\right]}{\partial r}}}_{g(r, x_P)}. \tag{6}$$

We illustrate r^N, which satisfies (6), graphically. As shown in Fig. 1, the platform's expected revenue is concave for $r \in (0, 1)$. Although the analytical expression of the optimal commission rate decision is implicitly given, the left-hand side of (6) remains constant at the potential market size of the online channel, a_O, while the right-hand side, defined as $g(r, x_P)$, varies with x_P. These two curves intersect at r^N. By analyzing the function $g(r, x_P)$, which essentially defines the platform's optimal commission rate, we observe the following results:

Lemma 2. *The platform's optimal commission rate r^N is a strictly increasing function of his private signal x_P:*

$$\frac{\partial r^N}{\partial x_P} = -\frac{\frac{\partial g(r, x_P)}{\partial x_P}}{\frac{\partial g(r, x_P)}{\partial r}} > 0.$$

Using the implicit function theorem, we can observe $\frac{\partial r^N}{\partial x_P}$ from the platform's commission rate optimality condition in (6). Lemma 2 states that the platform sets a higher commission rate as its private signal x_P increases. Consequently, the seller can infer that a high commission rate indicates a high value of the platform's private signal $\hat{x}_P$ even without direct information exchange. Specifically, the seller knows that the platform determines the commission rate to satisfy the optimality condition $g(r, \hat{x}_P) = a_O$. Therefore, based on the announced commission rate r^N, the seller can inversely deduce the platform's private signal $\hat{x}_P$, which satisfies $g(r^N, \hat{x}_P) = a_O$, and use this inferred signal to update her beliefs about market uncertainty. As a leader, the platform anticipates this inference process and incorporates it into its commission rate decision, establishing a rational expectation equilibrium.

Although the seller cannot observe the platform's private signal x_P, she attempts to infer it from the announced commission rate r. Similar to Li and Zhang (2008), the seller's inference from r depends on her belief about the functional form of $r(x_P)$. As Lemma 2 indicates, $r(x_P)$ is a strictly increasing function of x_P. Moreover, since $\mathbb{E}\left(m \mid x_P\right)$ has a monotonic relationship with x_P, r is also increasing in $\mathbb{E}\left(m \mid x_P\right)$.

Proposition 2. *Given the platform's announced commission rate r, the seller infers the platform's signal x_P as $\hat{x}_P$ in a rational equilibrium, where $\hat{x}_P$ satisfies:*

$$\hat{x}_P = \frac{\sqrt{L_1^2 - 4L_2 L_3} - L_1}{2L_2},$$

$$\begin{aligned} L_1 =& B_P \left\{ \left(A^N + rA'^N + rA_S^N \mu_P \frac{\partial x_P}{\partial r}\right)\left(1 - b_O A_S^N\right) \right. \\ &\left. + \left(A_S^N + A_S'^N\right)\left(a_O - b_O A^N\right) \right\}, \\ &- rb_O B_P \left\{ \left(A_S^N A'^N + (A_S^N)^2 \mu_P \frac{\partial x_P}{\partial r} + A^N A_S^N\right) \right\}, \\ L_2 =& B_P^2 \left\{ \left(A_S^N + rA_S'^N\right)\left(1 - b_O A_S^N\right) - rb_O A_S^N A_S'^N \right\}, \\ L_3 =& \left(A^N + rA'^N + rA_S^N \mu_P \frac{\partial x_P}{\partial r}\right)\left(a_O - b_O A^N\right) \\ &- rb_O A^N \left(A'^N + A_S^N \mu_P \frac{\partial x_P}{\partial r}\right), \end{aligned}$$

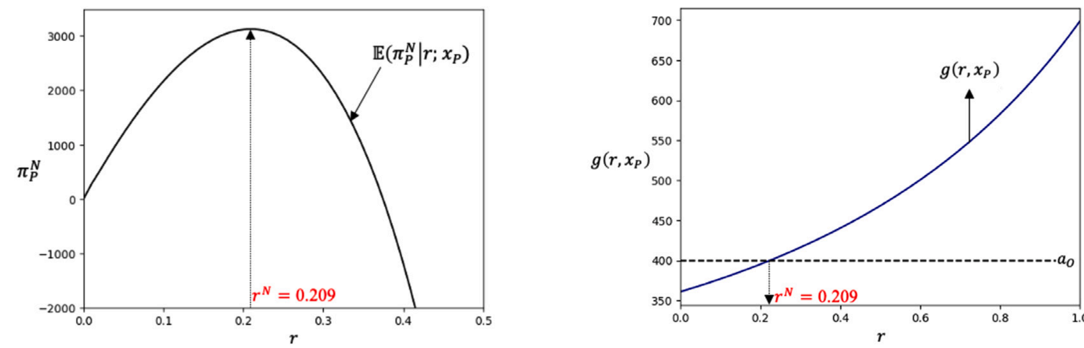
A^N, A_S^N, and μ_P are given in Proposition 1, $B_P = \frac{v_P}{v + v_P}$, $A'^N = \frac{a_D b_O - a_O b_D}{2[b_O(1-r) + b_D]^2}$ and $A_S'^N = \frac{b_O - b_D}{2[b_O(1-r) + b_D]^2}$.

Proposition 2 states that $\hat{x}_P$ is a rational belief about x_P in equilibrium when the seller knows that the platform would take x_P into consideration in setting r. With this information, the seller updates her belief about market uncertainty using both signals (x_S and $\hat{x}_P$ via r) and retrieves the corresponding selling price p^N by substituting $\hat{x}_P$ (as given in Proposition 2) into Proposition 1. The inference effect implies that, as the seller adopts the inferred signal to maximize her expected profit, i.e., $\hat{x}_P = f(r) = \frac{\sqrt{L_1^2 - 4L_2 L_3} - L_1}{2L_2}$, the platform anticipates the seller's price reaction as $\mathbb{E}(p^N|x_P) = A^N + A_S^N \mu_S \frac{v_P}{v + v_P} x_P + A_S^N \mu_P f(r)$. Hence, marginal changes in r influence the seller's inferred signal, $\hat{x}_P = f(r)$, which in turn incentivizes the platform to adjust its optimal commission rate—either increasing or decreasing it accordingly.

4.2. With mutual information exchange (W)

Now the platform can make use of the seller's private information x_S to determine its commission rate r in order to maximize its expected revenue. Hence, the platform can anticipate the seller's reaction

(where $a_O = 400, a_D = 1000, b_O = 1, b_D = 1, x_P = 0, \nu = 1,$ and $\nu_S = 1$)



(a) Platform's Expected Revenue

(b) Optimal Commission Rate Condition

Fig. 1. Platform's expected revenue and equilibrium commission rate condition.

function p for any given commission rate r and determine its optimal commission rate r^W when there is information exchange. Note that with mutual information exchange, the platform knows that the seller no longer infers its signal through r, as x_P is directly exchanged. Meanwhile, the platform receives the seller's signal x_S, allowing it to symmetrically observe the seller's price reaction function. The seller's reaction function, using both signals, is:

$$p^W(r, x_S, x_P) = A^W + A_S^W \mu_S x_S + A_S^W \mu_P x_P, \tag{7}$$

where $A^W = A^N$ and $A_S^W = A_S^N$ from Proposition 1. When the seller and the platform exchange their private signals x_S and x_P bilaterally, both parties can leverage these two signals (x_S, x_P) to obtain a more accurate forecast of the market condition m, as shown in Lemma 1. From (7), the seller's best response price $p^W(r, x_P, x_S) = A^W + A_S^W \mu_S x_S + A_S^W \mu_P x_P$ depends on both signals (x_S, x_P) and the commission rate r.

Optimal Commission Rate r^W. By substituting the seller's best response price $p^W(r, x_P, x_S)$ into the platform's expected revenue $\mathbb{E}(\pi_P^W | r; x_P, x_S)$, we get:

$$\mathbb{E}(\pi_P^W | r; x_P, x_S) = r \cdot p^W(r, x_S, x_P) \cdot \left(a_O + \mathbb{E}\left(m \mid x_P, x_S\right) - b_O \cdot p^W(r, x_S, x_P)\right), \tag{8}$$

where $\mathbb{E}\left(m \mid x_P, x_S\right)$ is given in Lemma 1 and $p^W(r, x_P, x_S)$ is stated in (7). By considering the first-order condition for r, the platform's optimal commission rate r^W solves the following equation:

$$a_O = \underbrace{b_O \frac{p^W(r, x_S, x_P)^2 + r\frac{\partial p^W(r, x_S, x_P)^2}{\partial r}}{p^W(r, x_S, x_P) + r\frac{\partial p^W(r, x_S, x_P)}{\partial r}} - \frac{\nu_P}{\nu + \nu_S + \nu_P} x_P - \frac{\nu_S}{\nu + \nu_S + \nu_P} x_S}_{k(r, x_S, x_P)}. \tag{9}$$

Similar to the optimal commission rate condition under no information exchange, $g(r, x_P)$ from (6), with information exchange $k(r, x_S, x_P)$ defines the platform's optimal commission rate. Since the left-hand sides of Eqs. (6) and (9) are identical — both representing the online channel market size, a_O, with and without information exchange — and since $g(r, x_P)$ and $k(r, x_S, x_P)$ are both convex and increasing functions in r (as shown in Fig. 1(b)), it follows that, for given x_P and x_S, $g(r, x_P) > k(r, x_S, x_P) \Leftrightarrow r^N < r^W$, and $g(r, x_P) < k(r, x_S, x_P) \Leftrightarrow r^N > r^W$. Furthermore, because the information sharing or exchange decision is made ex-ante, before the seller and the platform observe their private signals x_S and x_P, we can compare the expectations of the right-hand sides — $\mathbb{E}\left[g(r, x_P) \mid x_P\right]$ and $\mathbb{E}\left[k(r, x_S, x_P) \mid x_S, x_P\right]$ — to equivalently analyze $\mathbb{E}[r^N]$ and $\mathbb{E}[r^W]$ for comparative statics.

Note that, with information exchange, the platform observes the seller's signal x_S; hence, the reaction function is directly observed by the platform as $p^W\left(r, x_S, x_P\right)$. In contrast, without information exchange, the platform cannot access x_S and instead anticipates the seller's reaction based on the expected price $\mathbb{E}\left[p^N \mid x_P\right]$. Although the analytical expressions for the optimal commission rates appear to be intricate, we can derive the following outcomes for cases where the information precision of each player is either significantly high or low. These outcomes provide us with some structural results that can be examined numerically for intermediate values. Lemma 3 compares the platform's commission rates under both scenarios, with and without information exchange.

Lemma 3. *Suppose the base demand for the online channel is sufficiently large (i.e., $\frac{a_O}{a_D} > \frac{b_O}{b_D}$). Then, the platform would charge a lower commission rate with mutual information exchange, such that $\mathbb{E}\left[r^W\right] < \mathbb{E}\left[r^N\right]$, when either the platform or the seller has highly precise or imprecise information: $\nu_S \to 0$, $\nu_P \to 0$, $\nu_S \to \infty$, or $\nu_P \to \infty$. Conversely, if the seller's base demand for the direct sales channel exceeds that for the online channel ($\frac{a_O}{a_D} \le \frac{b_O}{b_D}$), then information exchange leads to a higher expected commission rate, $\mathbb{E}\left[r^W\right] > \mathbb{E}\left[r^N\right]$.*

When the platform's information precision is relatively higher than the seller's (for example, when $\nu_S \to 0$ or $\nu_P \to \infty$), the seller places greater weight on the platform's private signal x_P when setting her price p. This is reflected in the conditions where $\mu_S = 0$ (for $\nu_S \to 0$) and $\mu_P = 1$ (for $\nu_P \to \infty$), as stated in Proposition 1. In this case, if the players do not exchange information, the seller infers the platform's signal through r^N and incorporates this inferred signal $\hat{x}_P$ to set her selling price. As stated in Lemma 3, when the seller's base demand from the direct sales a_D is larger than the sales generated by the platform's common marketplace a_O, the platform charges a lower commission rate without information exchange. This results in the seller lowering her selling price. In particular, Proposition 1 and the sensitivity analysis of r suggest that with a relatively large direct sales channel market size ($\frac{a_O}{a_D} < \frac{b_O}{b_D}$), a lower commission rate from the platform leads to a lower selling price of the seller ($\frac{\partial p^N}{\partial r} > 0$). Moreover, as Lemma 2 shows, the seller's inferred signal $\hat{x}_P$ decreases when the platform announces a lower r^N, which leads to an even further reduction in the seller's price p^N. Given these two factors — the seller reducing the price in response to a lower inferred signal and the platform's own incentives to lower r — the platform has a strong motivation to reduce its commission rate under no information exchange, resulting in the outcome $\mathbb{E}\left[r^N\right] \le \mathbb{E}\left[r^W\right]$.

In case the seller's market demand is primarily generated by the platform's common marketplace (e.g., $\frac{a_O}{a_D} \ge \frac{b_O}{b_D}$), charging a high commission rate brings two opposite effects: (1) the higher the commission rate, the lower the selling price, as $\frac{\partial p^N}{\partial r} \le 0$ if $\frac{a_O}{a_D} \ge \frac{b_O}{b_D}$, and (2) a high commission rate indicates a high value of the inferred signal $\hat{x}_P$ for the seller, leading to an increase in the selling price due to the seller's reaction to the inferred signal $\hat{x}_P$ (see Proposition 1). Since the selling price p^N decreases as r^N increases, even though the magnitude of the reduction is partially moderated by the inference effect (e.g., $\frac{\partial A^N}{\partial r} = \frac{a_D b_O - a_O b_D}{2[b_O(1-r)+b_D]^2}$ and $\frac{\partial A_S^N}{\partial r} = \frac{b_O - b_D}{2[b_O(1-r)+b_D]^2}$), the platform under no information exchange is incentivized to charge a higher commission rate compared to when there is information exchange: $\mathbb{E}\left[r^N\right] > \mathbb{E}\left[r^W\right]$.

In addition, when the seller's private signal is considerably more precise relative to the platform's precision (i.e., $v_S \to \infty$ or $v_P \to 0$), the inference effect through the platform's announcement of r^N becomes negligible, as the seller relies more on her own signal ($p^N = A^N + A_S^N \mu_S x_S$). The platform, therefore, cannot use r^N to signal to the seller, as the seller gives little weight to the inferred signal from the platform. However, under information exchange, the variance of demand randomness can be significantly reduced, while the seller's price reaction function in x_S becomes symmetric. Moreover, when the platform's own signal precision is low ($v_P \to 0$), the platform cannot conjecture the seller's private signal x_S incorporated in the price reaction function to set an optimal commission rate, as $\mathbb{E}(p^N|x_P) = A^N$. This means that without information exchange, the equilibrium commission rate r^N is set by market factors and remains constant, regardless of x_P. When exchanging signals, however, the platform can use the seller's signal x_S to improve its forecast accuracy of market uncertainty, as exhibited in Lemma 1, due to variance reduction. Further, the platform now incorporates the seller's relatively precise signal x_S into its commission rate decision. Due to the reduction in variance and signal adaptation, the platform can lower its commission rate by exchanging information: $\mathbb{E}\left[r^W\right] < \mathbb{E}\left[r^N\right]$, especially when the seller's information precision is relatively high (i.e., $v_S \to \infty$ or $v_P \to 0$) and when the online channel is larger ($\frac{a_O}{a_D} > \frac{b_O}{b_D}$).

Ex-ante Expected Profit and Revenue Functions. Without information exchange, the commission rate r^N that maximizes the expected revenue, as given in (5), depends on the platform's own signal x_P, while the seller's optimal price depends on $r^N(x_P)$ and x_S. On the other hand, with information exchange, the seller's ex-ante expected profit and the platform's ex-ante expected revenue are determined by the platform's optimal commission rate r^W, based on both signals x_S and x_P, and the corresponding seller's best response price $p^W\left(r^W, x_S, x_P\right)$. For both cases, the seller's ex-ante expected profits and the platform's ex-ante expected revenues are:

$$
\begin{aligned}
&\Pi_S^N \equiv \mathbb{E}_{x_S,x_P}\left\{\pi_S^N\left(r^N, p^N\left(r^N, x_S, \hat{x}_P\right)\right)\right\} \quad \text{and} \\
&\Pi_P^N \equiv \mathbb{E}_{x_S,x_P}\left\{\pi_P^N\left(r^N, p^N\left(r^N, x_S, \hat{x}_P\right)\right)\right\} \\
&\Pi_S^W \equiv \mathbb{E}_{x_S,x_P}\left\{\pi_S^W\left(r^W, p^W\left(r^W, x_S, x_P\right)\right)\right\} \text{ and} \\
&\Pi_P^W \equiv \mathbb{E}_{x_S,x_P}\left\{\pi_P^W\left(r^W, p^W\left(r^W, x_S, x_P\right)\right)\right\}.
\end{aligned} \tag{10}
$$

Since obtaining closed-form solutions for the equilibrium commission rate is analytically intractable, a direct comparison of ex-ante expected profits is not feasible. Nevertheless, two consistent patterns emerge from extensive numerical experiments, as stated in Observations 1 and 2.

Observation 1. *The platform benefits more under no information exchange than with mutual information exchange. However, the seller prefers mutual information exchange when the online market demand is sufficiently large (i.e.,* $\frac{a_O}{a_D} > \frac{b_O}{b_D}$*).*

As Fig. 2 illustrates, the platform is better off under no information exchange. This is because the platform can use the commission rate r^N to signal its private information x_P to its advantage. While the benefits associated with the seller's inference effect are amplified when the platform's information precision is high (Figs. 2(a) and 2(c)), the platform's benefit under no information exchange diminishes as the seller's information becomes more precise, as illustrated in Figs. 2(b) and 2(d). On the other hand, information exchange benefits the seller when the online channel's base demand is sufficiently large ($\frac{a_O}{a_D} > \frac{b_O}{b_D}$). The seller's incentive to exchange information increases as the platform offers more precise information, v_P, as shown in Fig. 2(a). However, as her own information precision v_S is high, the seller's incentive to exchange information decreases (see Fig. 2(b)), in contrast to the platform's incentive to exchange information.

When the seller's direct sales channel demand is relatively large ($\frac{a_O}{a_D} \leq \frac{b_O}{b_D}$), information exchange does not benefit either player because the seller's major revenue is generated outside the platform's common marketplace (see Figs. 2(c) and 2(d)). From the platform's perspective, the seller's price is primarily influenced by the direct sales market demand a_D. Additionally, for the seller, the benefit of reducing the variability of market uncertainty by receiving the platform's private signal x_P through information exchange cannot compensate for the loss incurred by revealing her private signal x_S and informing the platform of her price reaction function in x_S. Nonetheless, if the seller's information precision is significantly high, the benefit of remaining silent under no information exchange decreases for both players, as shown in Fig. 2(d).

In Fig. 2, we find that a win-win is not possible unless there is a side payment. Often, the seller benefits, but the platform can never benefit. In some cases, information exchange can result in a lose-lose situation (as shown in Figs. 2(c) and 2(d)), making no information exchange (N) the equilibrium outcome. The equilibrium of not exchanging information is explained as follows: both players are better off without information exchange when the seller's demand is primarily generated by the direct sales channel ($\frac{a_O}{a_D} \leq \frac{b_O}{b_D}$). In particular, an increase in base demand in the direct sales channel leads to a more dramatic price increase compared to an increase in online sales channel demand, as $\frac{\partial p}{\partial a_O} = \frac{1-r}{2(b_O(1-r)+b_D)}$ and $\frac{\partial p}{\partial a_D} = \frac{1}{2(b_O(1-r)+b_D)}$. This implies that, with a large direct sales base demand, the seller sets a high selling price, influenced solely by market factors (i.e., a_O, a_D, b_O, and b_D), and extracts her profit primarily through the direct sales channel. Since setting a high selling price and reducing the demand generated via the online market is unfavorable to the platform, it lowers the commission rate to encourage the seller to lower the price, generating more demand through the online channel as the direct channel's base demand grows.

In particular, the seller sets a lower selling price when (1) the platform announces a lower r or (2) observes low values of market signals (x_S and x_P). While exchanging information requires truthfully revealing the value of x_P, without information exchange, the platform can make the seller infer a lower signal, $\hat{x}_P$, by announcing a reduced r^N. As Lemma 3 states, a reduced commission rate r^N causes p^N to decrease significantly, as the seller's reaction function is influenced by both the lower r^N and the smaller inferred value of $\hat{x}_P$ when $\frac{a_O}{a_D} \leq \frac{b_O}{b_D}$. Therefore, the platform has more effective control over the seller's price by remaining silent. Especially when the inference effect is more pronounced (i.e., $v_P \to \infty$ or $v_S \to 0$), the effect of manipulation through r^N is maximized, while the impact of not incorporating the seller's signal x_S is trivial under no information exchange, as shown in Figs. 2(c) and 2(d). Consequently, the platform observes a higher ex-ante expected revenue under no exchange.

From the seller's perspective, the reluctance to exchange information arises from the fact that the platform can exploit her private information, x_S, to set an unfavorable commission rate, r^W, by revealing the price reaction function tied to x_S and thereby extracting more revenue from the online channel. However, when the inference effect is strong (i.e., $v_P \to \infty$ or $v_S \to 0$), the seller's price reaction function for a given r remains the same: $p(r) = \frac{a_O(1-r)+a_D}{2(b_O(1-r)+b_D)} + \frac{2-r}{2(b_O(1-r)+b_D)}\mu_P x_P$, regardless of information exchange. Consequently, the value of possessing private information for the seller is minimal; however, she benefits from the platform's reduced commission rate, r^N, under no information exchange. Conversely, when the inference effect is weak (i.e., $v_S \to \infty$ or $v_P \to 0$), the seller's price is highly dependent on x_S, making the value of retaining private information maximized under no information exchange. This is because (1) the platform cannot effectively manipulate r^N to induce the seller to infer $\hat{x}_P$ in its favor, as

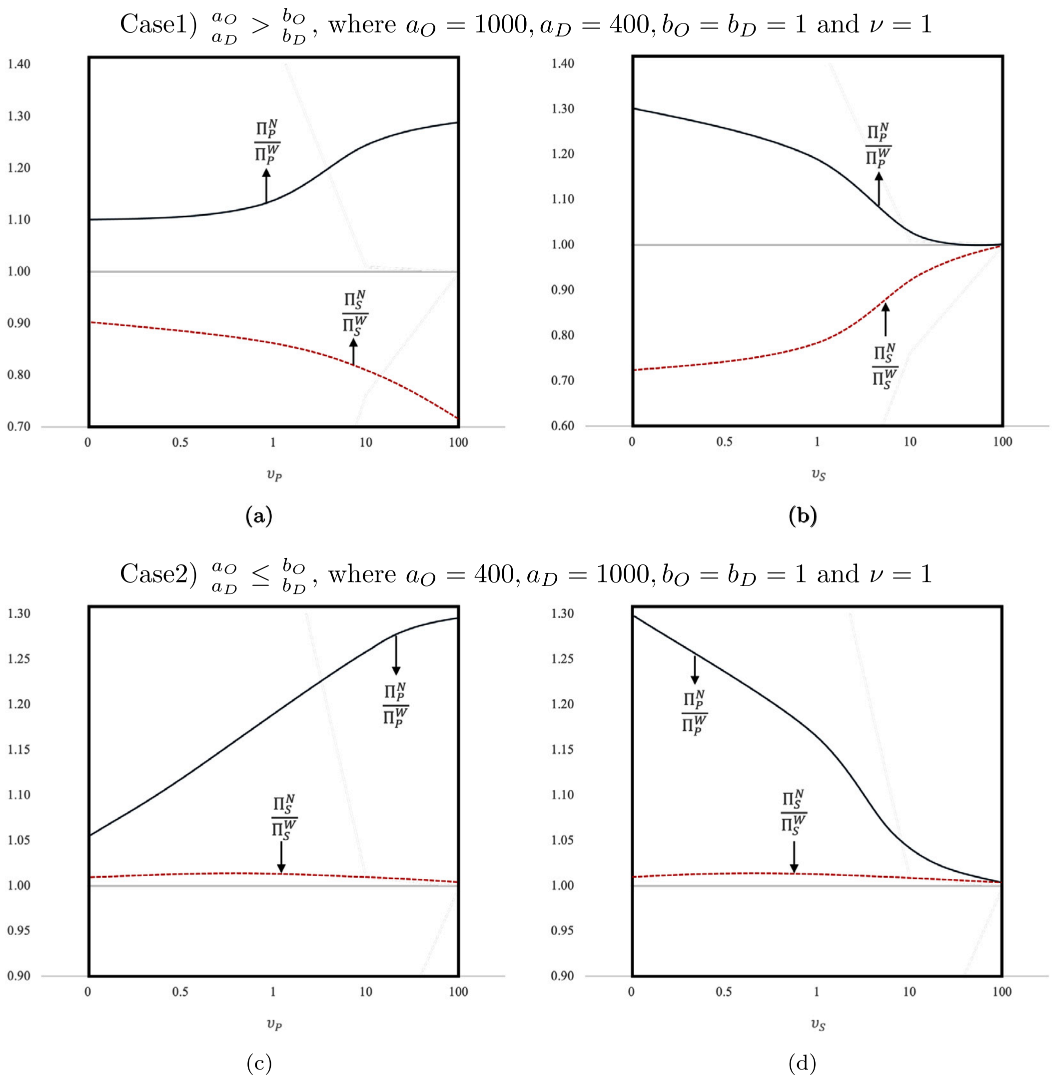


Fig. 2. Ex-ante expected revenue for the platform and Profit for the seller.

the seller places greater weight on her own signal x_S, and (2) the seller prevents the platform from leveraging x_S to set a more advantageous r^N. Consequently, in both scenarios, the seller benefits more by not exchanging information.

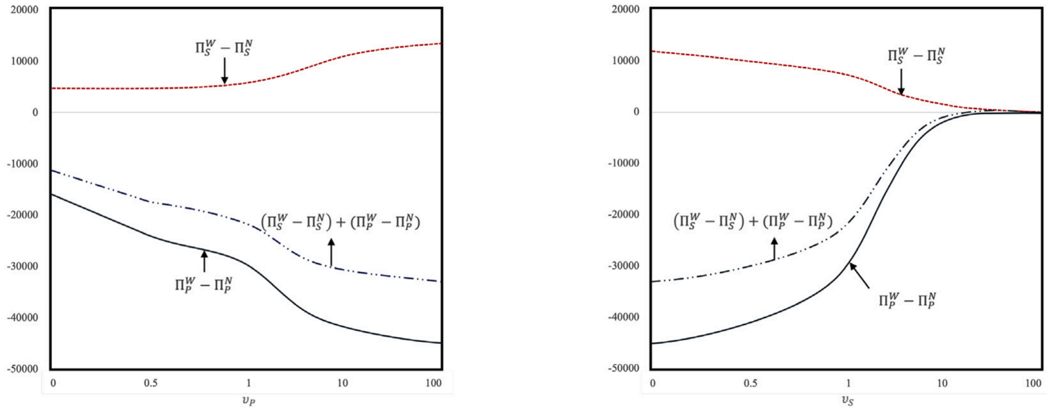
Observation 2. *When the online channel demand is high (i.e., $\frac{a_O}{a_D} > \frac{b_O}{b_D}$) and the seller possesses precise information (i.e., $v_S \to \infty$), the seller can incentivize the platform to engage in mutual information exchange by offering a side payment.*

The platform generally lacks an incentive to mutually exchange information with the seller. However, the seller benefits from such an exchange when the base demand in the online channel through the platform's common marketplace is relatively larger than the base demand in the direct sales channel (i.e., $\frac{a_O}{a_D} > \frac{b_O}{b_D}$). Fig. 3 shows that the seller obtains a higher ex-ante expected profit ($\Pi_S^W \ge \Pi_S^N$), while the platform is worse off under information exchange ($\Pi_P^W \le \Pi_P^N$). This implies that the seller can offer a side payment to entice the platform to exchange information mutually if $\Pi_S^W - \Pi_S^N > \Pi_P^N - \Pi_P^W$.

Specifically, when the platform's information precision is significantly higher than the seller's (i.e., $v_P \to \infty$), the seller's incentive to receive information from the platform increases. However, the platform's reluctance to exchange information also rises sharply, as shown in Fig. 3(a). As the platform's precision improves, the total surplus generated by information exchange, $(\Pi_S^W - \Pi_S^N) + (\Pi_P^W - \Pi_P^N)$, diminishes, indicating that the seller's benefit from exchanging information does not offset the platform's loss; hence, a side payment is not feasible. On the other hand, Fig. 3(b) illustrates that as the seller's information precision becomes significantly higher than the platform's (i.e., $v_S \to \infty$), the benefit of information exchange declines, even though the seller still experiences a positive gain (i.e., $\Pi_S^W \ge \Pi_S^N$). In contrast, the platform's incentive for remaining silent decreases considerably, leading to a situation where the platform becomes almost indifferent between exchanging information and not exchanging it (i.e., $\Pi_P^W \approx \Pi_P^N$). Consequently, when $v_S \to \infty$, the seller can offer a minimal side payment to the platform to achieve information exchange.

In summary, the rationale behind the no information exchange equilibrium is based on (1) the platform's strategic use of the seller's inference effect by setting a lower r^N, and (2) the seller's reluctance to reveal the price reaction function (which incorporates x_S) symmetrically under information exchange, in order to prevent the platform from exploiting x_S and extracting additional revenue from the online channel. Conventionally, the platform often shares its private information, x_P, to help the seller set a better price, p, and increase revenue from the online market, given their symbiotic relationship. In our model, however, we show that revealing x_P does not necessarily increase revenue in the online market when the direct market dominates the seller's market structure. Specifically, as the seller infers the signal through r^N, no information exchange is preferable to mutual exchange.

(where $a_O = 1000, a_D = 400, b_O = b_D = 1$ and $\nu = 1$)



(a) (b)

Fig. 3. Comparison between no and with information exchange.

Although the seller might prefer to receive x_P in exchange for her signal x_S, the value of having x_P (thus reducing the variability of market uncertainty) under exchange and the value of keeping x_S under no exchange (thus preventing the platform from setting an unfavorable r) creates a trade-off. This trade-off can make no information exchange the equilibrium under certain conditions.

Although information exchange does not inherently benefit both players and can result in incentive misalignment (or even a lose-lose scenario), our numerical analysis shows that if the seller's information precision is relatively high (i.e., $v_S \to \infty$), the seller can provide a side payment to encourage mutual information exchange. Thus, mutual information exchange cannot be implemented without a side payment from the benefiting player. Beyond mutual exchange, it remains unclear whether unidirectional sharing — where the platform only reveals x_P to the seller, or the seller only shares x_S with the platform — can align incentives, benefiting both parties. Therefore, in the following section, we investigate cases of unilateral sharing and explore the corresponding incentives for each player.

5. Unilateral information sharing scenarios

In practice, information is often shared in a unidirectional manner upon request. We now explore how unidirectional information sharing affects the benefits for both the seller and the platform. We examine whether information sharing by a single player is sufficient to ensure mutual benefit or if incentive misalignment issues, as observed in Section 4, persist. If misalignment occurs, we also consider who might offer a side payment and under which circumstances.

5.1. Platform's information sharing (PI)

We first examine the scenario where the platform unidirectionally shares its private signal, x_P, with the seller, while the seller retains her private signal, x_S. In this case, the seller's corresponding expected profit and reaction function are as follows:

$$\begin{aligned}\mathbb{E}\left(\pi_S^{PI} \mid p; r, x_S, x_P\right) &= p(1-r)\cdot\left(a_O + \mathbb{E}\left(m \mid x_S, x_P\right) - b_O\cdot p\right)\\ &\quad + p\cdot\left(a_D + \mathbb{E}\left(m \mid x_S, x_P\right) - b_D\cdot p\right)\\ p^{PI}(r, x_S, x_P) &= A^{PI} + A_S^{PI}\mu_S x_S + A_S^{PI}\mu_P x_P,\end{aligned} \tag{11}$$

where $A^{PI} = A^N$ and $A_S^{PI} = A_S^N$ from Proposition 1. Note that since the seller has access to both signals, x_S and x_P, her price reaction function remains the same as in the scenario where both players mutually exchange information. However, unlike in mutual exchange, the platform lacks knowledge of x_S. Therefore, the platform's expectation of the seller's price reaction function is:

$$\mathbb{E}(p^{PI}|x_P) = A^{PI} + A_S^{PI}\mu_S\frac{v_P}{v+v_P}x_P + A_S^{PI}\mu_P x_P. \tag{12}$$

Similar to (4), the platform has no access to the seller's signal x_S. However, upon sharing its information, the platform knows that the seller's coefficient associated with the platform's market signal, $A_S^{PI}\mu_P$, is now based on the actual signal x_P rather than an inferred signal $\hat{x}_P$ obtained through r. Based on the expectation of the seller's reaction function $\mathbb{E}(p^{PI}|x_P)$, the expected revenue of the platform is

$$\mathbb{E}(\pi_P^{PI}|r; x_P) = r\cdot\mathbb{E}\left[p^{PI}\left(a_O + \frac{v_P}{v+v_P}x_P - b_O p^{PI}\right) \mid x_P\right], \tag{13}$$

where $\mathbb{E}\left(p^{PI} \mid x_P\right)$ is defined in (12). As the seller does not infer any signal through r^{PI} but directly uses the platform's shared signal x_P, the platform's equilibrium derivation follows a backward induction, while $\mathbb{E}(x_S \mid x_P) = \mathbb{E}(m \mid x_P)$.

5.2. Seller's Information Sharing (SI)

Now, suppose the seller unidirectionally shares her market information x_S with the platform, while the platform retains its own information x_P. In this scenario, the seller infers the platform's signal $\hat{x}_P$ based on the announced commission rate r set by the platform.

$$\begin{aligned}\mathbb{E}\left(\pi_S^{SI} \mid p; r, x_S, \hat{x}_P\right) &= p(1-r)\cdot\left(a_O + \mathbb{E}\left(m \mid x_S, \hat{x}_P\right) - b_O\cdot p\right)\\ &\quad + p\cdot\left(a_D + \mathbb{E}\left(m \mid x_S, \hat{x}_P\right) - b_D\cdot p\right)\\ p^{SI}(r, x_S, \hat{x}_P) &= A^{SI} + A_S^{SI}\mu_S x_S + A_P^{SI}\mu_P\hat{x}_P,\end{aligned} \tag{14}$$

where $A^{SI} = A^N$ and $A_S^{SI} = A_S^N$ from Proposition 1. Since the platform knows x_S and the seller's inference of $\hat{x}_P$, the reaction function $p^{SI}(r, x_S, \hat{x}_P)$ is fully observable by the platform. The platform's expected revenue is:

$$\begin{aligned}\mathbb{E}(\pi_P^{SI}|r; x_S, x_P) &= r\cdot p^{SI}(r, x_S, \hat{x}_P)\\ &\quad\cdot\left\{a_O + \mathbb{E}\left(m \mid x_S, x_P\right) - b_O\cdot p^{SI}(r, x_S, \hat{x}_P)\right\}.\end{aligned} \tag{15}$$

Lemma 4. *Suppose the base demand for the direct sales channel is sufficiently large (i.e., $\frac{a_O}{a_D} < \frac{b_O}{b_D}$). Then, the platform charges a higher expected commission rate when it shares information, i.e., $\mathbb{E}\left[r^{SI}\right] < \mathbb{E}\left[r^{PI}\right]$, in cases where either the platform or the seller has highly precise or imprecise information: $v_S \to 0$, $v_P \to 0$, $v_S \to \infty$, or $v_P \to \infty$. Conversely, if the seller's base demand for the online channel is larger than that for the direct sales channel ($\frac{a_O}{a_D} \geq \frac{b_O}{b_D}$), the platform's information sharing leads to a lower expected commission rate, i.e., $\mathbb{E}\left[r^{PI}\right] \leq \mathbb{E}\left[r^{SI}\right]$.*

Table 2
Price reaction function by information policies, where $B_P = \frac{v_P}{v+v_P}$.

Case	Seller's reaction function	Platform's observation of seller's price
N	$p^N = A^N + A_S^N \cdot (\mu_S x_S + \mu_P \hat{x}_P)$	$\mathbb{E}(p^N \| x_P) = A^N + A_S^N \cdot (\mu_S B_P x_P + \mu_P \hat{x}_P)$
W	$p^W = A^W + A_S^W \cdot (\mu_S x_S + \mu_P x_P)$	$p^W(x_S, x_P) = A^W + A_S^W \cdot (\mu_S x_S + \mu_P x_P)$
PI	$p^{PI} = A^{PI} + A_S^{PI} \cdot (\mu_S x_S + \mu_P x_P)$	$\mathbb{E}(p^{PI} \| x_P) = A^{PI} + A_S^{PI} \cdot (\mu_S B_P x_P + \mu_P x_P)$
SI	$p^{SI} = A^{SI} + A_S^{SI} \cdot (\mu_S x_S + \mu_P \hat{x}_P)$	$p^{SI}(x_S, \hat{x}_P) = A^{SI} + A_S^{SI} \cdot (\mu_S x_S + \mu_P \hat{x}_P)$

N: No Exchange, W: With Exchange, PI: Platform Sharing, and SI: Seller Sharing.

Similar to Lemma 3, when the base demand in the platform's common marketplace is sufficiently large (i.e., $\frac{a_O}{a_D} \geq \frac{b_O}{b_D}$), allowing the seller to infer the platform's private signal $\hat{x}_P$ leads the platform to increase its expected commission rate compared to the case where the platform directly reveals the signal x_P to the seller, i.e., $\mathbb{E}\left[r^{PI}\right] \leq \mathbb{E}\left[r^{SI}\right]$. This occurs because the seller's price reaction function responds in two ways: (1) with a higher commission rate r, the seller lowers the selling price p to capture more revenue from the online market, but (2) under the inference effect, a higher commission rate r signals a high value of $\hat{x}_P$, leading the seller to increase the price p. Ultimately, due to this balancing effect, when the platform withholds its information (i.e., SI) and $\frac{a_O}{a_D} \geq \frac{b_O}{b_D}$, it charges the seller a higher commission rate.

On the other hand, when the base demand in the direct sales market dominates (i.e., $\frac{a_O}{a_D} < \frac{b_O}{b_D}$), there is little opportunity to generate substantial revenue from the platform's common marketplace. In this case, the platform's primary interest is ensuring that the seller's price p is not set too high, to prevent the seller from earning the majority of her profit through the direct sales channel. To encourage a lower selling price, the platform sets a low commission rate. Since the inference effect induces the seller to lower the price when the platform charges a lower commission rate, the platform has an additional incentive to further reduce the commission rate. As a result, in this scenario, the platform's expected commission rate is lower when information is shared, i.e., $\mathbb{E}\left[r^{SI}\right] < \mathbb{E}\left[r^{PI}\right]$.

At its core, different information sharing and exchange scenarios influence the seller's price reaction function and, consequently, the platform's observation of the seller's price reaction. The reaction functions for these four different scenarios (i.e., N, W, PI, and SI) are summarized in Table 2. When the platform does not disclose its signal x_P, the seller infers the platform's signal, denoted as $\hat{x}_P$, from the announced commission rate r and incorporates this information into her pricing decision, as seen in cases N and SI. Conversely, when the seller withholds her signal x_S, the platform, announcing its commission rate before the seller's price, cannot directly infer the seller's signal. Instead, the platform uses the expected value of x_S based on its observed signal x_P, given by $\mathbb{E}(x_S|x_P) = \frac{v_P}{v+v_P}x_P = B_P x_P$ in cases N and PI. The impact of asymmetric information is most evident when neither player exchanges information. However, even unilateral information sharing can impede a player's ability to make optimal decisions. For example, under scenario PI, the platform relies on $B_P x_P$ instead of x_S, while under SI the seller bases her decisions on the inferred signal $\hat{x}_P$ rather than the actual signal x_P.

Although Lemmas 3 and 4 demonstrate the impact of the seller's reaction functions on the platform's expected commission rate decisions under different information policies — showing how the platform leverages the seller's inference effect to set the optimal commission rate — the platform can only partially observe the seller's price reaction function under certain information policies (i.e., N and PI). As a result, the effect of a specific information sharing or exchange policy on the expected profits (or revenues) for both players remains ambiguous. In the next section, we compare the ex-ante expected profits of the seller and the platform to assess the equilibrium information policy.

6. Comparison of information exchange and sharing

The seller sets a price p for her omnichannel (i.e., direct and online sales markets) based not only on the private signals regarding market uncertainty (x_S and x_P) but also on the relative base demand sizes of the two channels (a_O and a_D), as shown in Proposition 1. The following sensitivity analysis demonstrates that the seller's response to the platform's commission rate varies depending on the relative base demand sizes of the two channels. Specifically, when, $\frac{a_O}{a_D} \leq \frac{b_O}{b_D}$, $\frac{\partial p}{\partial r} \geq 0$, and when $\frac{a_O}{a_D} > \frac{b_O}{b_D}$, $\frac{\partial p}{\partial r} < 0$. Consequently, the effect of the commission rate decision under different information policies changes based on the underlying market structures, as outlined in Lemmas 3 and 4. With this observation, we analyze the ex-ante expected profit of the seller and the platform for each information sharing/exchange policy (N, W, PI, and SI) under two distinctive market structures: Case 1, where $\frac{a_O}{a_D} > \frac{b_O}{b_D}$, and Case 2, where $\frac{a_O}{a_D} \leq \frac{b_O}{b_D}$. Although direct analytical comparisons with W are intractable, we perform these comparisons numerically, as illustrated in Figs. 4 and 6. This approach provides a comprehensive understanding, in addition to the analytical results presented in Lemmas 5 and 6.

When the base demand for the online channel exceeds that of the direct sales channel ($\frac{a_O}{a_D} > \frac{b_O}{b_D}$), obtaining more precise information through the platform's information sharing becomes crucial for both parties, as the main revenue stream now comes from the platform's common marketplace. This scenario intensifies the conflict of interest regarding information sharing and exchange decisions between the two players. For instance, Figs. 4(a) and 4(b) demonstrate that the platform achieves its highest ex-ante expected revenue when the seller unilaterally shares information, and its lowest revenue when the platform shares its information unilaterally. Conversely, the seller's ex-ante expected profit is highest when the platform unilaterally shares information, while the seller's profit is lowest when she shares the information unilaterally, as shown in Figs. 4(c) and 4(d). Thus, both parties prefer the other to share information unilaterally while withholding their own signals.

Lemma 5. *Suppose the base demand for the online channel is sufficiently large (i.e., $\frac{a_O}{a_D} > \frac{b_O}{b_D}$) and the seller holds precise private information $(v_S \to \infty)$. Then, it holds that $\Pi_S^{PI} - \Pi_S^N \geq \Pi_P^N - \Pi_P^{PI}$. Hence, the seller can afford to offer a side payment to entice the platform to support unilateral information sharing (PI).*

Although information sharing leads to the platform's lowest expected revenue, it yields the seller's highest expected profit (see Fig. 4). Hence, the seller may seek to incentivize the platform to share information (i.e., PI). Specifically, if the seller's gain from unilateral sharing outweighs the platform's loss, the seller can offer a side payment, creating a win-win scenario (i.e., $\Pi_S^{PI} - \Pi_S^N \geq \Pi_P^N - \Pi_P^{PI}$). When the platform has highly precise information ($v_P \to \infty$), its reluctance to share increases, making the side payment insufficient to incentivize sharing, as $\Pi_S^{PI} - \Pi_S^N < \Pi_P^N - \Pi_P^{PI}$ (see Fig. 5(a)). However, when the seller possesses precise information ($v_S \to \infty$), although the seller's loss under no information exchange is reduced, the platform becomes indifferent between N and PI. In this case, the seller can offer a minimal side payment to induce the platform to unilaterally share, as depicted in Fig. 5(b).

Lemma 6. *Suppose the base demand for the direct sales channel is sufficiently large (i.e., $\frac{a_O}{a_D} \leq \frac{b_O}{b_D}$) and the seller has precise private information ($v_S \to \infty$). Then, unilateral information sharing by the seller (SI) benefits both the platform and the seller such that $\Pi_P^{SI} \geq \Pi_P^N$ and $\Pi_S^{SI} \geq \Pi_S^N$.*

Whilst the platform generally prefers to conceal its private information from the seller in order to exploit the inference effect (i.e., $\Pi_P^{SI}/\Pi_P^N > \Pi_P^W/\Pi_P^{PI}$), it can still benefit from the seller's inference effect when the seller unilaterally shares private information

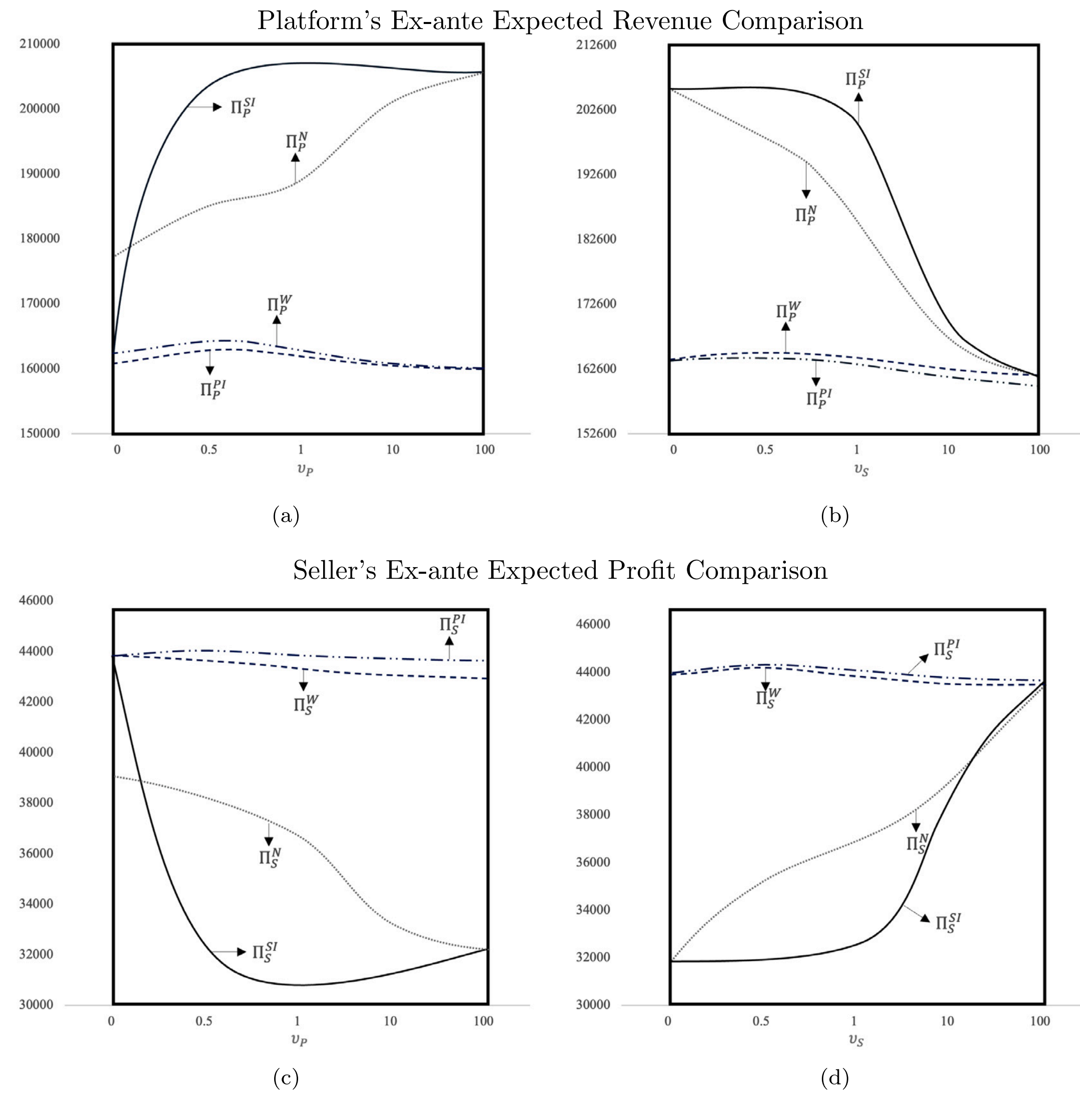


Fig. 4. Case (1) $\frac{a_O}{a_D} > \frac{b_O}{b_D}$, where $a_O = 1000, a_D = 400, b_O = b_D = 1,$ and $\nu = 1$.

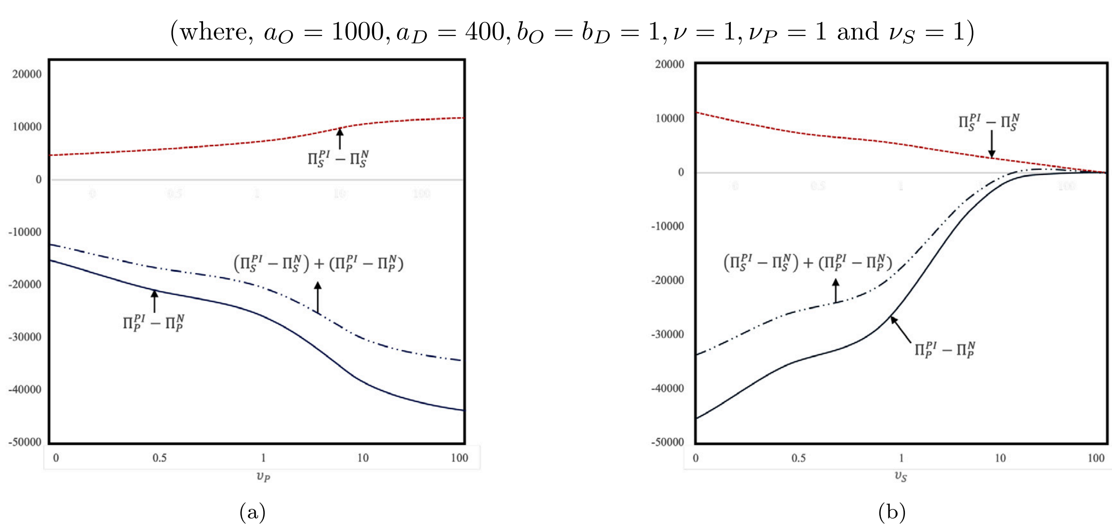


Fig. 5. Comparison of platform's unilateral information sharing when $\frac{a_O}{a_D} > \frac{b_O}{b_D}$.

under SI, as the seller remains unaware of the platform's information. Furthermore, the seller's precise information sharing (i.e., $v_S \to \infty$) reduces demand uncertainty, enabling the platform to secure a higher ex-ante expected revenue compared to scenarios with no information exchange. This implies that the platform prefers access to the seller's information over a setting with no information sharing (i.e., $\Pi_P^{SI} > \Pi_P^N$), particularly when the seller generates most of their revenue from the direct sales channel rather than through the platform (i.e., $\frac{a_O}{a_D} \leq \frac{b_O}{b_D}$), as shown in Figs. 6(a) and 6(b).

For the seller, when she has precise information (i.e., $v_S \to \infty$), she relies solely on her own signal to anticipate market potential across both channels ($q_O = a_O + x_S - b_O \cdot p$ and $q_D = a_D + x_S - b_D \cdot p$), independent of the information-sharing policy. In such a situation, the seller's primary interest is in incentivizing the platform to lower its commission rate. By sharing her information, the platform lowers its commission rate even further than in the case of no information exchange, $\mathbb{E}(r^{SI}|x_S) \leq \mathbb{E}(r^N|x_P)$, as the platform can fully observe the seller's reaction function and significantly reduce the variability of demand uncertainty via x_S. Consequently, when the seller's information is highly precise ($v_S \to \infty$), she prefers to actively reveal her information to the platform (SI), as illustrated in Fig. 6(d), to prevent the platform from setting a suboptimal commission rate based on an inaccurate expectation of her price reaction. Consequently, with the seller's precise information, both players benefit from the seller's unilateral information sharing, as $\Pi_P^{SI} > \Pi_P^N$ and $\Pi_S^{SI} > \Pi_S^N$.

7. Extension: Preannouncement of commission rate

While many large platforms frequently adjust their commission rates, one could argue that these rates are typically determined as long-term decisions, whereas market information and sellers' pricing strategies tend to fluctuate more dynamically. For example, Temu applies a predefined commission rate — referred to as a referral fee — on each sale made through its platform, typically ranging from 2% to 5%. To reflect such settings, we extend our framework by modeling the commission rate as a strategic variable that is "preannounced" to the market and fixed before any information-sharing decisions occur. The seller then sets an optimal price based on a privately observed market signal.

In such a setting, the platform does not utilize private signals to set its commission rate r. Consequently, receiving the seller's information, x_S, becomes irrelevant. However, since the platform earns a commission as a proportion of the seller's revenue, it may have an incentive to unilaterally share its private signal, x_P. This suggests that when the commission rate is predetermined, the platform is effectively "passive", as it does not leverage the seller's information x_S. Nevertheless, sharing its signal, x_P, with the seller can impact the seller's price decision, potentially leading to higher revenue for the platform. Moreover, when the commission rate is predefined, the seller can no longer infer the platform's private signal, $\hat{x}_P$, because she knows that the platform's market signal does not affect its strategic decision on the commission rate.

7.1. No information sharing

Expected Profit of the Seller *without Inference Effect*. When the platform's commission rate is predefined, the seller's total expected profit from both channels is given by:

$$\begin{aligned}\mathbb{E}\left(\bar{\pi}_S^N \mid p; x_S, r\right) &= p(1-r)\cdot\left(a_O + \mathbb{E}\left(m \mid x_S\right) - b_O \cdot p\right) \\ &\quad + p\cdot\left(a_D + \mathbb{E}\left(m \mid x_S\right) - b_D \cdot p\right)\end{aligned} \tag{16}$$

Compared to (3), it is evident that under no information sharing, the seller cannot infer the platform's private signal x_P through r. Consequently, the seller's optimal price decision relies entirely on her own signal, without any information revelation from the platform, and is given by:

$\bar{p}^N = A^N + A_S^N B_S x_S$, where A^N, A_S^N from Proposition 1, and $B_S = \frac{v_S}{2(v+v_S)}$.

Expected Revenue of the Platform. Given the seller's optimal price $\bar{p}^N$, the platform's expected revenue is expressed as:

$$\mathbb{E}(\bar{\pi}_P^N|x_P,x_S) = r\cdot\bar{p}^N(x_S)\cdot\left(a_O + \mathbb{E}\left(m \mid x_P\right) - b_O\cdot\bar{p}^N(x_S)\right). \tag{17}$$

Although the platform does not share its private signal, it still observes x_P, which it uses to compute $\mathbb{E}\left(m \mid x_P\right)$. This allows the platform to determine its expected revenue, which can later be compared to the revenue under information sharing.

Ex-ante Expected Profit and Revenue Function. As the information sharing of x_P occurs before the players observe their private signals x_S and x_P, let $\overline{\Pi}_S^N$ denote the seller's ex-ante expected profit and $\overline{\Pi}_P^N$ denote the platform's ex-ante expected revenue without information sharing:

$$\begin{aligned}\overline{\Pi}_S^N &= A^N\frac{a_O(1-r)+a_D}{2} + A_S^N\frac{(2-r)}{2}\frac{B_S}{v} \text{ and } \overline{\Pi}_P^N \\ &= r\left\{A^N(a_O - A^N) + A_S^N\frac{B_S}{v}\left(B_P - b_O A_S^N\right)\right\},\end{aligned} \tag{18}$$

where A^N and A_S^N are given in Proposition 1, $B_S = \frac{v_S}{v+v_S}$, and $B_P = \frac{v_P}{v+v_P}$.

7.2. With platform's information sharing

When the platform unilaterally shares its signal x_P with the seller, the seller's optimal price $\bar{p}^{PI}$ is determined by utilizing both signals, (x_S, x_P), similar to the analysis under PI in Section 5.1, with r being predefined. Since the seller's expected profit function is defined as

$$\begin{aligned}&\mathbb{E}\left(\bar{\pi}_S^{PI} \mid p; x_S, x_P, r\right) = p(1-r)\cdot\left(a_O + \mathbb{E}\left(m \mid x_S, x_P\right) - b_O\cdot p\right) \\ &\quad + p\cdot\left(a_D + \mathbb{E}\left(m \mid x_S, x_P\right) - b_D\cdot p\right),\end{aligned}$$

the seller's optimal price is $\bar{p}^{PI} = p^{PI}$ from (11).

Platform's Expected Revenue. The platform's expected revenue, $\mathbb{E}(\bar{\pi}_P^{PI}|x_P,x_S)$, after sharing its private signal x_P with the seller, is defined as follows:

$$\mathbb{E}(\bar{\pi}_P^{PI}|x_P,x_S) = r\cdot\bar{p}^{PI}(x_S,x_P)\cdot\left(a_O + \mathbb{E}\left(m \mid x_P\right) - b_O\cdot\bar{p}^{PI}(x_S,x_P)\right). \tag{19}$$

Ex-ante Seller's Expected Profit and Platform's Expected Revenue. We denote $\overline{\Pi}_S^{PI}$ as the seller's ex-ante expected profit and $\overline{\Pi}_P^{PI}$ as the platform's ex-ante expected revenue with information sharing. The ex-ante expected profits of the seller and the platform, when the platform shares its information x_P, are expressed as follows:

$$\begin{aligned}\overline{\Pi}_S^{PI} &= A^{PI}\frac{a_O(1-r)+a_D}{2} + A_S^{PI}\frac{(2-r)}{2}\frac{v_S+v_P}{v(v+v_S+v_P)} \\ \overline{\Pi}_P^{PI} &= r\left\{A^{PI}(a_O - A^{PI}) + A_S^{PI}\frac{1}{v}\left(B_P - b_O A_S^{PI}\frac{v_S+v_P}{v+v_S+v_P}\right)\right\},\end{aligned} \tag{20}$$

where A^{PI} and A_S^{PI} are given in (11). By using the expressions from (18) and (20), we compare the ex-ante expected gain (or loss) of each player when the platform shares its private information, x_P.

Lemma 7. *By sharing x_P with the seller, the platform creates the following value:*

1. *The seller always benefits from receiving the platform's private signal x_P because her ex-ante expected profit is higher with information*

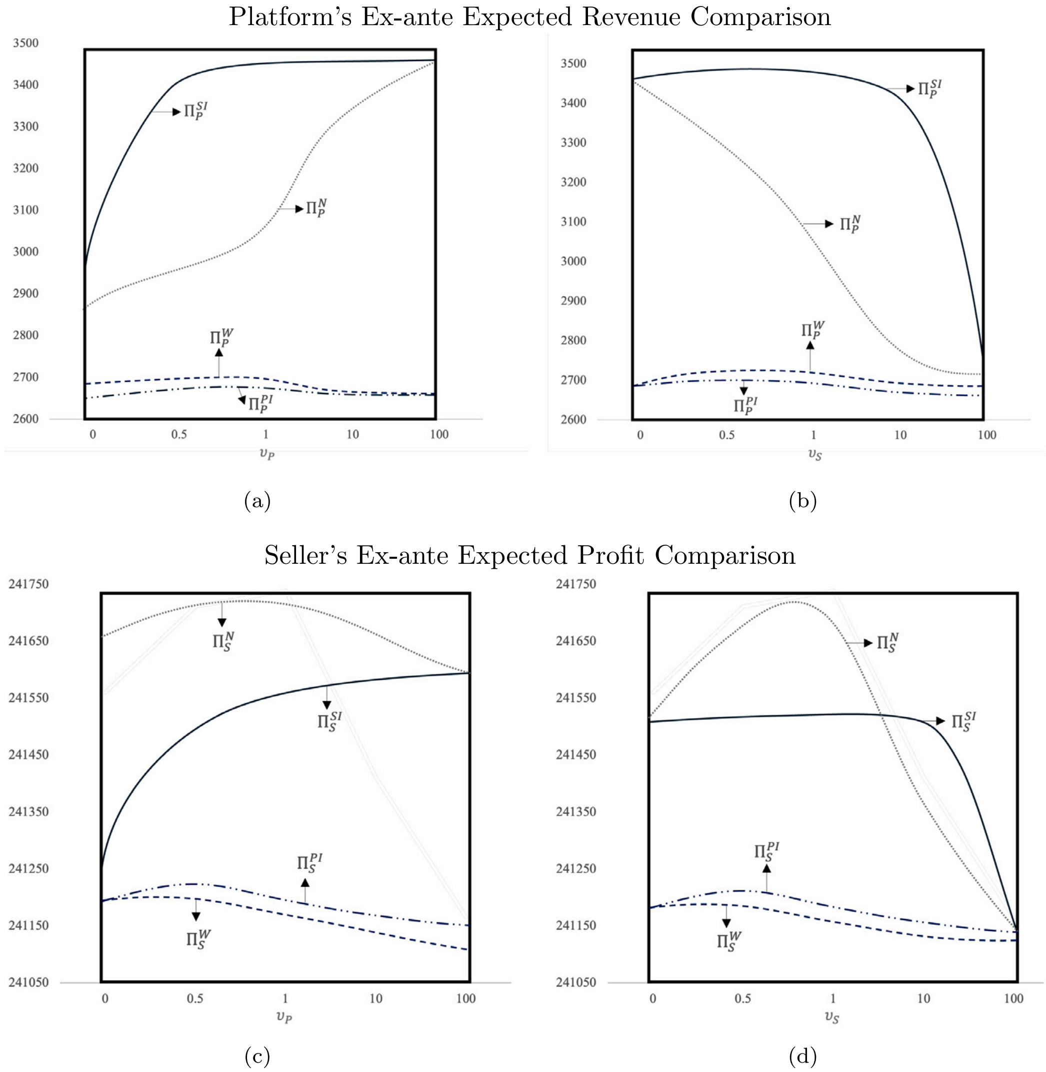


Fig. 6. Case (2) $\frac{a_O}{a_D} \le \frac{b_O}{b_D}$, where $a_O = 400, a_D = 1000, b_O = b_D = 1$ and $v = 1$.

sharing than in the case of no information sharing; i.e., $\overline{\Pi}_S^{PI} \ge \overline{\Pi}_S^{N}$, *where*

$$\overline{\Pi}_S^{PI} - \overline{\Pi}_S^{N} = \frac{(2-r)^2}{4[b_O(1-r)+b_D]} \left\{ \frac{v_P}{\left(v+v_S+v_P\right)\left(v+v_S\right)} \right\} > 0.$$

2. *The platform is better off sharing its private signal* x_P *with the seller when its preannounced commission rate* r *satisfies* $0 \le r \le \frac{2[v_S b_O + (v+v_S+v_P) b_D]}{(v+2v_S+v_P) b_O}$. *When this condition holds, the platform's ex-ante expected revenue with information sharing is higher than in the case of no information sharing; i.e.,* $\overline{\Pi}_P^{PI} \ge \overline{\Pi}_P^{N}$, *where*

$$\overline{\Pi}_P^{PI} - \overline{\Pi}_P^{N} = \frac{2-r}{2[b_O(1-r)+b_D]} \frac{v_P}{v+v_S} \times \left\{ \frac{1}{v+v_P} - \frac{b_O(2-r)}{2[b_O(1-r)+b_D]} \frac{1}{v+v_S+v_P} \right\} > 0.$$

Lemma 7 states that the platform's information sharing always benefits the seller when it preannounces its commission rate. Moreover, although the platform's information sharing benefit is conditional on the information precision and price sensitivity of the two channels, when it possesses highly precise information (i.e., $v_P \to \infty$), it is clearly better off sharing, as $\overline{\Pi}_P^{PI} - \overline{\Pi}_P^{N} = \frac{2-r}{2[b_O(1-r)+b_D]}$. Recognizing that the seller gains surplus from the platform's information sharing, the platform may demand a fixed side payment of $K^* = \overline{\Pi}_S^{PI} - \overline{\Pi}_S^{N}$, effectively extracting the entire benefit the seller obtains from the information sharing. Alternatively, the platform could introduce a differentiated commission rate scheme under the sharing policy.

Optimal Commission Rate of the Platform under Sharing and no Sharing. A rational platform would adjust the commission rate when sharing information to ensure it also benefits from sharing, while still ensuring the seller's ex-ante expected profit. Let the commission rate without information sharing be denoted by $\bar{r}^N$, which is the solution to the following: $\max_{\bar{r}^N} \overline{\Pi}_P^{N}\left(\bar{r}^N; x_P\right)$, where $\overline{\Pi}_P^{N}$ is given in (18). Defining the platform's commission rate under information sharing as $\bar{r}^{PI}$, it charges this commission rate by satisfying the following conditions:

$$\begin{aligned} &\max_{\bar{r}^{PI}} \overline{\Pi}_P^{PI}\left(\bar{r}^{PI} | x_P\right) \\ &\text{subject to:} \quad \overline{\Pi}_P^{PI}\left(\bar{r}^{PI} | x_P\right) \ge 0 \qquad (PC) \\ &\overline{\Pi}_P^{PI}\left(\bar{r}^{PI} | x_P\right) \ge \overline{\Pi}_P^{N}\left(\bar{r}^{N} | x_P\right) \qquad (IC) \\ &\overline{\Pi}_S^{PI}\left(\bar{r}^{PI} | x_P, x_S\right) \ge \overline{\Pi}_S^{N}\left(\bar{r}^{N} | x_S\right) \qquad (IS) \end{aligned} \tag{21}$$

The participation constraint (PC) ensures the platform's positive ex-ante revenue by charging $\bar{r}^{PI}$. The incentive compatibility constraint (IC) ensures the platform benefits from information sharing by charging $\bar{r}^{PI}$. With information surplus constraint (IS), the platform ensures that the adjusted commission rate under information sharing, $\bar{r}^{PI}$, is not excessive so that the seller benefits from information sharing.

Lemma 8. *When the platform provides information sharing, it consistently sets a higher commission rate for the seller compared to the case of no information sharing (i.e., $\bar{r}^N \leq \bar{r}^{PI}$), but it does not exceed $\bar{r}_{tol} = \frac{-A_2-\sqrt{A_2^2-4A_1A_3}}{2A_1}$. Therefore, the platform charges the seller $\min(\bar{r}^{PI}, \bar{r}_{tol})$ for information sharing, where*

$$A_1 = a_O^2 + \frac{v_S + v_P}{2v\left(v + v_S + v_P\right)},$$

$$A_2 = a_O^2\left(1 + 2\bar{r}^N - \bar{r}^{N^2}\right) + a_D\left(2a_O\bar{r}^N - a_D\right) + \frac{4\left(v_S + v_P\right)}{v\left(v + v_S + v_P\right)} - \frac{(2 - \bar{r}^N)v_S}{2v\left(v + v_S\right)},$$

$$A_3 = -(a_O + a_D)^2 + 2\bar{r}^N(1 - \bar{r}^N) + 4\bar{r}^N a_O a_D + \frac{2\left(v_S + v_P\right)}{v\left(v + v_S + v_P\right)} - \frac{(2 - \bar{r}^N)v_S}{v\left(v + v_S\right)}.$$

In general, when the platform shares private information, it can impose a higher commission rate on the seller ($\bar{r}^N \leq \bar{r}^{PI}$). However, to ensure that the seller accepts this offer, the seller's ex-ante expected profit under the commission rate with information sharing must be at least as favorable as it would be without sharing. Therefore, the platform must consider the maximum tolerable commission rate for the seller, which satisfies: $\overline{\Pi}_S^{PI}\left(\bar{r}_{tol}\right) \geq \overline{\Pi}_S^{N}\left(\bar{r}^N\right)$. As illustrated in Fig. 7(a), when the platform optimizes its commission rate with information sharing, it imposes a higher commission rate on the seller, paired with the corresponding information policy: $(PI, \bar{r}^{PI})$ and $(N, \bar{r}^N)$. Notably, as the precision of the platform's information increases, it can charge an even higher commission rate under information sharing. Although the seller may have to pay a higher commission to the platform, Fig. 7(d) shows that the information-sharing contract still benefits the seller, as the value of receiving the platform's information offsets the increased commission rate. As Fig. 7(b) illustrates, the seller's benefit is greater than the platform's gain from sharing its information. Hence, the platform charges the optimal commission rate $\bar{r}^{PI}$ without considering $\bar{r}_{tol}$ in the numerical example and obtains a higher ex-ante expected profit, as shown in Fig. 7(c). Therefore, by pre-announcing its commission rate before the market signal is realized, the platform can create a win-win scenario by offering a two-part tariff tied to its information-sharing decision, especially when the platform has precise information.

8. Conclusion

We present a stylized game-theoretic model to explore the potential value derived from bilateral information exchange or unilateral sharing. Our analysis focuses on investigating the impact of different information policies on the optimal commission rate decision made by the platform and the selling price decision made by the seller. Our results reveal that, in general, both the seller and the platform prefer to remain silent rather than engage in mutual information exchange when the seller's revenue is primarily generated through the direct sales channel. When the direct sales channel market demand dominates the online channel, the seller sets a high selling price to maximize profit from the direct sales channel. When the platform's private information is revealed through information exchange, the platform loses the ability to exploit the inference effect to induce a lower selling price from the seller, making it prefer no information exchange. Furthermore, due to the lower commission rate, the seller is better off without information exchange.

If the seller possesses precise information about market uncertainty, unilateral information sharing by the seller can lead to a win-win outcome compared to the case with no information exchange. From the platform's perspective, it benefits from the inference effect: by withholding its own information while leveraging the seller's information, it can make better commission rate decisions. As a result, the platform always prefers that the seller shares her information rather than withholding it. On the other hand, when the seller shares her precise signal, she anticipates that the platform will place significant weight on it, thereby the marginal value of the platform's private information and effectively creating a setting of symmetric information. Therefore, when the seller's information precision is sufficiently high, granting the platform access to her private signal – thus enabling a lower commission rate – ultimately benefits the seller when the direct market demand is larger than that of the online channel.

Furthermore, we demonstrate that "mutual information exchange" cannot fully resolve the incentive misalignment arising from "unilateral information sharing". Specifically, the benefits of mutual exchange are not as substantial as those from cases where either the seller receives the platform's information unilaterally or the platform receives the seller's information unilaterally. This is because mutual exchange eliminates two strategic advantages: the platform loses the ability to employ the inference effect by remaining silent, and the seller forfeits the benefit of preventing the platform from observing her price reaction function, which contains her private information. These additional "frictions" compared to unilateral sharing may explain why mutual information exchange is not commonly applied in practice. Lastly, when the platform's commission rate is a long-term decision and pre-announced to the seller (making it independent of market signals), unilateral information sharing by the platform always benefits the seller. Given this benefit to the seller, the platform's implementation of a two-part tariff results in a higher optimal commission rate with information sharing compared to the commission rate without sharing. Even with the higher commission rate, information sharing can still create a win-win scenario for both parties.

Based on our findings, several practical implications emerge. First, sellers — such as a small apparel store that relies heavily on a marketplace like Amazon for revenue — may be willing to pay a higher commission or offer side payments in exchange for access to the platform's proprietary market signals. Platforms like Amazon, which benefit from network effects and visibility into competitive dynamics, possess valuable insights into market trends. Sharing this information can help sellers better navigate demand uncertainty in the online channel, aligning incentives for both parties. Second, when a seller — such as a well-established clothing brand — joins a marketplace like Amazon for the first time, sharing the seller's private market data can be mutually beneficial, even if demand from the seller's direct sales channel still outweighs that from the platform. The platform gains insight into broader market behavior, while the seller benefits from enhanced visibility and coordination. Lastly, even when a seller prefers mutual information exchange — especially if most of her revenue comes from the platform — the platform may not have a reciprocal incentive to share its data.

Our stylized model has several limitations that warrant further investigation. First, our model does not account for the competition effect across different channels, as it assumes that the seller offers the same price for both direct and online sales channels. However, in practice, consumer utility varies across channels, and a competition effect may arise, allowing the seller to discriminate prices. While the choice model in multi-channel retailing is beyond the scope of this study, it has received considerable attention and would be valuable to incorporate into future research on information sharing. Second, we do not consider multiple sellers operating within a shared online marketplace. However, a key feature of common marketplaces is the presence of multiple sellers offering substitutable products at competing prices. The competition among sellers intensifies the analysis, making a model based on Bertrand's competition complex. Also, exploring the design of two distinct pricing schemes — one for commissions on sellers' sales and another for fees associated with market information acquisition — offers a promising direction for future research.

For technical simplicity, we adopt a linear demand function with market randomness following a normal distribution. However, exploring alternative forms of market randomness could provide additional

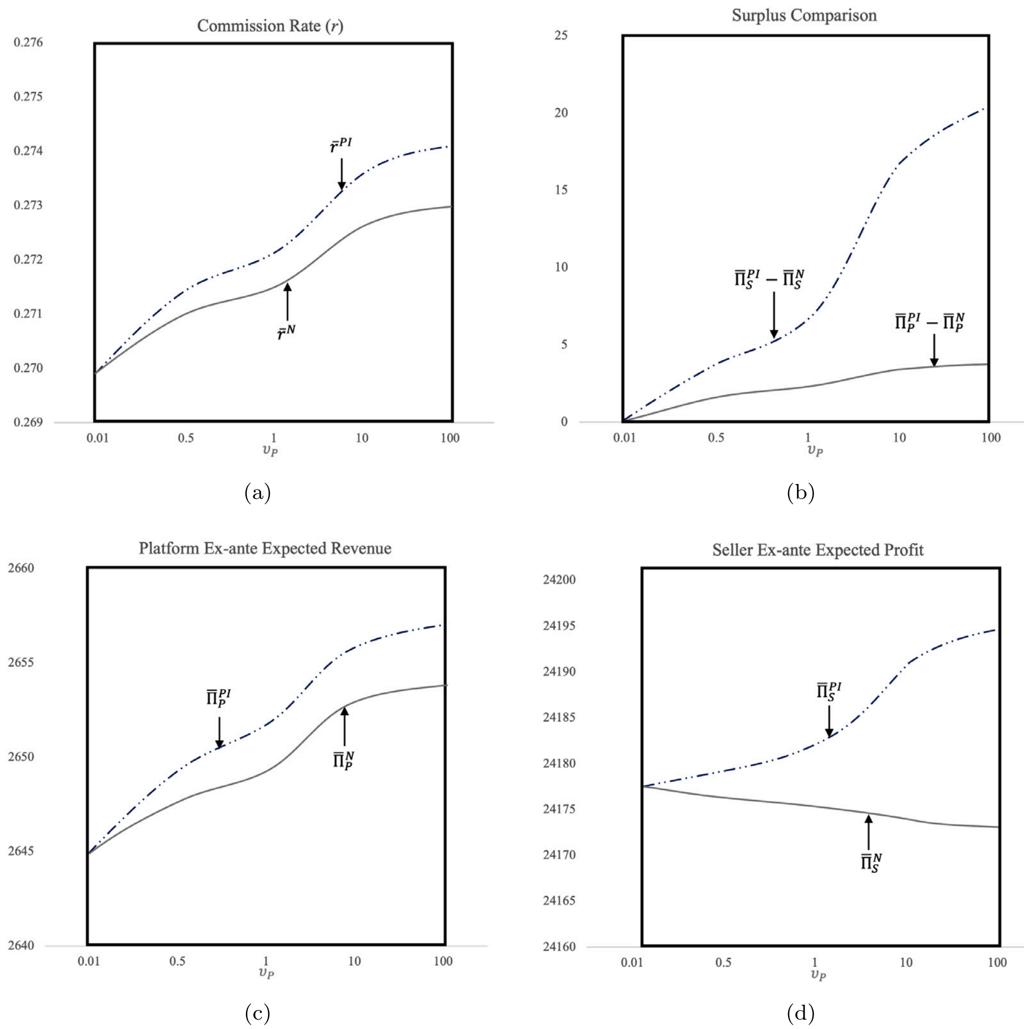


Fig. 7. $a_O = 400, a_D = 1000, b_O = b_D = 1, v = 1,$ and $v_S = 1$.

insights into the effects of information exchange and updates to prior beliefs. Future research could explore scenarios in which market uncertainty is generated independently for each sales channel, capturing the distinct characteristics of these channels. Different channels may be subject to varying competitive dynamics, such as logistical proximity and after-sales services. Lastly, we assume that the platform does not offer the same products as the seller, treating it as a pure marketplace, similar to TikTok Shop. While the platform acts as an agent in this context, many platforms also operate as resellers, selling products directly from manufacturers. To enrich the current analysis, it would be valuable to examine scenarios where the platform operates both as a reseller and an agent. This would involve investigating whether the incentives for unilateral information sharing or mutual exchange remain consistent when the platform sets its own selling price in the future.

CRediT authorship contribution statement

Eunji Lee: Writing – original draft, Visualization, Methodology, Conceptualization. **Christopher S. Tang:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Stefan Minner:** Writing – review & editing, Methodology.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ejor.2025.10.017.

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