Managing Freight Rejection in Supply Chains with Production Diseconomy: Information Sharing Strategies via Digital Freight Platforms

Ye Shi
School of Management, University of Science and Technology of China
hecules@ustc.edu.cn

Amir A. Alwan
Sheldon B. Lubar School of Business, University of Wisconsin–Milwaukee
aalwan@uwm.edu

Mengqi Liu
Business School of Hunan University
liumengqi163@126.com

Xiaohang Yue
Sheldon B. Lubar School of Business, University of Wisconsin–Milwaukee
xyue@uwm.edu

Supply chain operations frequently face disruptions due to freight rejection. Motivated by real-world practices, this paper develops a game-theoretical model to examine how digital freight platforms can share their private predictive information on the spot freight market to help supply chain companies improve their operations and mitigate freight rejection risks. Specifically, the model considers a digital freight platform that shares private information with a supply chain comprising a retailer (the shipper working directly with the platform) and a manufacturer, enabling them to adjust their decisions in anticipation of freight rejection. We address two key strategic questions faced by the platform: (i) how to share the private information, and (ii) how to choose the accuracy of the private information. Our findings reveal that, as upstream production diseconomies increase, the platform favors sharing information with both the retailer and manufacturer, rather than exclusively with the retailer. Moreover, as the supply chain becomes more sensitive to freight rejection, the platform benefits from improving the accuracy of the private information, with both the retailer's and the platform's net payoffs initially decreasing and then increasing. We further examine platform's information-sharing strategies in the context of competing supply chains and characterize its equilibrium information sharing formats. Interestingly, we find that as the competition intensity increases, the platform will decrease the accuracy of the private information within an equilibrium format; however, as the competition intensity further increases, the equilibrium formats will shift, leading the platform to have sudden stepwise improvements in the accuracy of its information. Finally, we observe that information sharing by digital freight platforms may have a negative spillover effect on other solutions aimed at reducing freight rejection.

Key words: digital freight platform, freight rejection, information sharing

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1. Introduction

1.1. Motivation

Modern supply chain logistics is increasingly affected by uncertain freight market conditions (Lee et al. 2015). A common phenomenon that exacerbates the impact of such uncertainty is *freight (load) rejection*, which is particularly prevalent in the context of truckload shipping (Scott et al. 2017). Typically, shippers in supply chains try to secure freight rates for transporting their goods (or materials) in advance by signing long-term freight contracts with carriers. When shippers need to transport their goods, they first tender load requests to their contracted carriers, who are expected to accept and haul the goods at the contracted rates. However, due to the lack of legally binding obligations in freight contracts, contracted carriers can opt to reject these requests. There is empirical evidence (e.g. Scott et al. (2017), Aryapadi et al. (2021), Acocella (2022)) indicating that a major reason for freight rejection is the carriers' opportunistic behavior in reserving their capacity for high spot (freight) rates, especially when the freight market is tight (i.e., freight demand exceeds supply). When freight rejection occurs, shippers are forced to find for-hire carriers from the spot (freight) market, often paying a significant spot premium of 35% above the contracted rate (Aemireddy and Yuan 2019, Scott et al. 2017).

Fortunately, the rise of digital freight platforms, such as Convoy (www.convoy.com) and Uber Freight (www.uberfreight.com), provides companies in supply chains with the opportunity to improve their operations in response to freight rejection. When freight rejection occurs, these platforms leverage advanced information technologies and matching algorithms to help companies in supply chains quickly locate alternative for-hire carriers (Miller et al. 2020, Zhou and Wan 2022). Moreover, digital freight platforms serve as data analytics centers and have superior private information on the spot freight market compared to those companies in supply chains. As a result, platforms like Convoy and Uber Freight have established information sharing programs to help companies in supply chains better anticipate freight rejection and make responsive adjustments in their operations. Specifically, the platforms can share information through two different strategies. First, some platforms, such as Uber Freight, provide Application Programming Interfaces (APIs) that allow companies in supply chains to access their private information. Second, other platforms, such as Convoy, offer APIs that enable companies to integrate private information with their own Transportation Management Systems (TMS) and Enterprise Resource Planning (ERP) systems (Freightos 2024, Pyzyk 2021). The second strategy for information sharing is evidently more flexible, as integration with companies' existing systems allows them (e.g., downstream retailers) to further share freight market data with their partners (e.g., upstream manufacturers) in the supply chain using Electronic Data Interchange (EDI).

The motivation for this work partially stems from a research collaboration with a leading digital freight platform in China[1]. Most partners directly working with the platform are downstream companies (e.g., retailers) in supply chains that use the platform's services in cases of freight rejection. Recently, this platform initiated a program to share predictive information about the spot freight market with its partners. However, the platform faces challenges in implementing the information sharing program. First, similar to Uber Freight and Convoy, the platform must choose between different strategies for information sharing. One strategy is referred to as *partial company-level information sharing*, under which only downstream retailers (i.e., the direct shippers) can access the platform's predictive information via APIs. Noting that this predictive information could also benefit upstream firms (e.g., manufacturers/suppliers) in the supply chain—who could use the information to adjust their wholesale prices by anticipating the impact of freight rejection on downstream retailing (Chen et al. 2016, 2019, Konur and Toptal 2012)—the platform can adopt another strategy called *full supply-chain-level information sharing.* This strategy allows downstream retailers to flexibly share predictive information with upstream manufacturers, for example, through API integration with the retailers' TMS or EPR systems. For brevity, we will refer to "partial company-level information sharing" as "partial information sharing" and to "full supply-chain-level information sharing" as "full information sharing" in the remainder of this paper. Second, the platform needs to carefully plan the accuracy of the predictive information when investing in the program. As the accuracy of the predictive information increases, information sharing helps supply chains gain a competitive edge by allowing them to adjust their operations in better anticipation of freight rejection, but it also requires the platform to spend more on collecting sample data from the spot freight market. In summary, several key issues relevant to the platform's practice of information sharing are as follows.

(a) How can we quantify the value of information sharing by a digital freight platform on companies in a supply chain, as well as for the platform itself, in the context of freight rejection?

(b) How does a digital freight platform choose the appropriate information sharing strategy (i.e., partial or full information sharing) when implementing its information sharing program?

(c) How does a digital freight platform optimize the accuracy of its predictive information? Should the platform invest more to improve the accuracy of its predictive information as supply chain competition intensifies?

Although these issues are motivated by the Chinese digital freight platform, they are relevant to digital freight platforms worldwide, including Convoy, Loadsmart, and Uber Freight. However, to the best of our knowledge, these practical problems are less addressed in the literature. To fill this

[1] For confidentiality reasons, the details about the platform are omitted.

research gap, we develop a game-theoretical model consisting of a supply chain and a digital freight platform. In the supply chain, a retailer sells goods to a Cournot-type market of customers and orders these goods from a manufacturer with production diseconomy. The production diseconomy, which refers to the phenomenon that the manufacturer's marginal production cost increases with production quantity, which is commonly used in the literature (Ha et al. 2011, Shang et al. 2016). It is well supported by empirical evidence in industries such as petroleum refining and auto making (Griffin 1972, Mollick 2004). The retailer also utilizes transportation services, typically provided by a contracted carrier, to move the procured goods from the manufacturer's facility to the retailer's site. However, the retailer may encounter freight rejection, depending on uncertain spot freight rates. If freight rejection occurs, the retailer finds a for-hire carrier through the platform and pays a spot rate to the for-hire carrier along with a brokerage fee to the platform. The platform has a private predictive signal about the spot rate and can share the signal with the supply chain, helping companies adjust their decisions in better anticipation of the rejection of the shipment. Moreover, the platform must choose between two information sharing strategies—either partial or full information sharing—and decide the prediction accuracy of the signal at costly efforts. We also extend the analysis by considering information sharing by the platform with two supply chains engaging in Cournot competition.

1.2. Main Findings

By exploring the single supply chain model, we first analyze the effect of information sharing by a digital freight platform on both firms in the supply chain and the platform itself. Compared to the baseline of no information sharing, we find that any degree of information sharing by the platform, whether partial or full, benefits relevant players by improving their operations in response to freight rejection, providing an explanation for the widespread use of these information sharing programs in practice. We then compare the platform's two information sharing strategies and find that, relative to partial information sharing, full information sharing generates more value for the manufacturer by enabling them to adjust the wholesale price but generates less value for the retailer and the platform due to the double marginalization effect. As a result, under side payments from the manufacturer to both the retailer and the platform, the platform's equilibrium choice is full information sharing only if the upstream production diseconomy is sufficiently large. Otherwise, the platform's equilibrium information sharing strategy is partial information sharing. We also demonstrate that the platform should improve the prediction accuracy of its own private signal as the retailer's sensitivity coefficient of freight rejection increases.

By analyzing the extended model that incorporates supply chain competition, we develop the conditions for the platform's equilibrium information sharing strategies for competing supply chains, depending on the production diseconomy and competition intensity. Generally, we find that the equilibrium information sharing strategy takes on three distinct formats: (a) symmetric partial information sharing (i.e., both supply chains adopt partial information sharing), (b) asymmetric mixed information sharing (i.e., one supply chain adopts full information sharing while the other adopts partial information sharing), and (c) symmetric full information sharing (i.e., both supply chains adopt full information sharing). As the upstream production diseconomy increases (or as competition intensity increases), the platform gradually changes its equilibrium information sharing format from (a) to (c), indicating a move toward more comprehensive information sharing across supply chains. Furthermore, we characterize the platform's optimal prediction accuracy decision. Notably, the optimal prediction accuracy decision exhibits a piecewise form as the platform changes equilibrium information sharing formats. Interestingly, we identify two significant impacts of supply chain competition on the platform's optimal accuracy decision. First, as competition intensity increases, the platform experiences sudden stepwise improvements in its prediction accuracy, reflected by two upward jumps in the optimal prediction accuracy as the platform transitions equilibrium information sharing formats from (a) to (c). Second, under every equilibrium information sharing format, the platform's prediction accuracy decision decreases as competition intensity increases.

1.3. Research Contributions

This paper contributes to the literature in the following ways. First, unlike existing studies focusing primarily on the role of digital freight platforms in matching freight demand and supply (Miller et al. 2020, Li et al. 2020, Zhou and Wan 2022), this work is the first to examine information sharing by digital freight platforms with companies in supply chains facing freight rejection risks. Our results show that information sharing by digital freight platforms improves the responsiveness of these companies to freight rejection and allows the platforms to effectively exploit the business value of their private information.

Second, in the literature (e.g., Scott et al. (2017), Acocella (2022)), some solutions (e.g., flexible freight contracts) have been proposed to manage freight rejection by reducing the probability of its occurrence. This paper complements the literature by introducing a novel approach that focuses on improving firms' responsiveness to freight rejection through information sharing. We also examine the interaction between the existing solutions and our new solution, observing a *negative spillover effect* of information sharing by digital freight platforms on the effectiveness of the existing solutions.

Third, previous studies (e.g., Ha et al. (2011), Shang et al. (2016)) have shown that the double marginalization effect plays an important role in the economic incentives for intra-supply-chain information sharing. This paper extends these studies by demonstrating that full information sharing by digital freight platforms with supply chains also leads to the double marginalization effect on the platform itself. As such, full information sharing needs to be induced through manufacturers' side payments only when their production diseconomy is sufficiently large. Interestingly, our results show that the equilibrium information sharing formats for competing supply chains can take the form of asymmetric mixed information sharing, which contrasts with previous findings that only symmetric information sharing formats arise (Ha et al. 2011). We also reveal the significant impact of supply chain competition on shifts in equilibrium information formats and optimal prediction accuracy decisions by digital freight platforms.

2. Literature Review

This paper is related to three streams of literature: (i) digital freight platforms, (ii) freight operations considering freight rejection, and (iii) supply chain information sharing.

Digital Freight Platforms. In recent years, digital freight (brokerage) platforms, also known as online freight exchange platforms, have garnered increasing interest from operations management researchers. Powered by advanced information technologies (such as mobile applications and the Internet of Things), these platforms enable shippers in supply chains to quickly locate for-hire (or private) carriers from the spot freight market, especially when they are rejected by their contract carriers. Most of the existing literature delves into the fundamental roles of digital freight platforms in addressing the matching or assignment problem, as well as how to improve the platform's performance of matching and assignment (Caplice 2007, Min and Kang 2021). For example, Miller et al. (2020) studies truck routing problems for digital freight platforms, assuming visibility of network-wide demand and supply information. Specifically, they model routing problems as a Markov decision process, taking into account multiple factors such as the probability of winning a load, future profitability, and the bidding order priority among possible load options. Li et al. (2020) study the problem of digital freight platforms jointly optimizing matching and pricing strategies for delivering to multiple retailers, and demonstrate the effectiveness of their proposed matching and pricing policy using empirical data from a famous freight platform in China. In addition to these theoretical studies, Zhou and Wan (2022) conduct an empirical study to examine the impact of digital freight platforms on the profitability and stock performance of incumbent road freight logistics companies, and find that only large trucking companies have significant positive profitability changes.

In supply chain logistics practice, digital freight platforms also play an informational role in sharing information with firms within supply chains to improve operations (Pyzyk 2021). However, this aspect is seldom addressed in the existing literature. This paper is among the few that investigates the impact of information sharing via digital freight platforms on supply chain operations in response to freight carrier rejection. This paper further discusses the strategic problems that digital freight platforms face when deciding on information sharing strategies and optimizing prediction accuracy. Our result complements the literature by providing insight into the conditions under which digital freight platforms implement various equilibrium information sharing strategies in both single and competing supply chains. Furthermore, we reveal the impact of the probability of freight rejection—a key parameter in the trucking industry—on the optimal prediction accuracy of digital freight platforms.

Freight Operations Considering Carrier Freight Rejection. There is a large body of operations management literature that discusses freight operations in supply chain logistics, examining the interaction between freight operations and classical retail, inventory and production operations (Lu et al. 2017, 2020, Boada-Collado et al. 2020). It is worth noting that most of these studies are based on the assumption that shippers can secure freight rates by entering into long-term contracts with contract carriers. However, since these long-term freight contracts lack legally binding obligations, shippers often encounter freight rejection in a tight freight market, resulting in high operational costs for the entire supply chain (Scott et al. 2017, Caplice 2021). Moreover, as freight market conditions grow increasingly uncertain and complex, the negative impact of freight rejection can no longer be ignored. Consequently, some researchers have begun to explore freight operations considering freight rejection. For example, Tsai et al. (2011) propose the use of derivative contracts in trucking as a means to hedge against uncertainty in transportation capacity and cost. Scott et al. (2017) carry out an empirical study to examine key operational and economic factors that drive and deter freight rejection. In particular, they suggest implementing a flexible freight pricing mechanism to mitigate freight rejection. Acocella (2022) propose a market-based freight contract, which dynamically updates the freight price between shippers and carriers to minimize the probability of freight rejection.

This paper also belongs to the literature on freight operations considering freight carrier rejection. Unlike the extant studies, we consider a new solution of improving supply chains' responsiveness to freight carrier rejection via digital freight platforms' information sharing. Our results demonstrate the effectiveness of this solution by quantifying the positive effect of information sharing on shippers (i.e., the retailer) relative to the benchmark of no information sharing. Interestingly, the result also shows that shippers' payoffs could increase as the probability of freight rejection increases under digital freight platforms' information sharing, which contradicts to the conventional wisdom that probability of freight rejection hurts shippers in the literature. We also examine the interaction between the existing solutions of suppressing probability of freight rejection and our solution of information sharing, and find that the existing solution can hurt shippers in the presence of information sharing.

Supply Chain Information Sharing. Information sharing in supply chains is a widely explored topic in the operations management community. Over the past decades, numerous papers have addressed a variety of issues related to information sharing, especially in the context of demand information sharing (Li 2002, Ha et al. 2011, Zhao et al. 2014, Chen and Deng 2015, Huang et al. 2018, Ha et al. 2022, Li and Zhang 2023). Recently, the emergence of platforms that possess superior information resources compared to individual firms in supply chains has led some researchers to investigate issues related to platform information sharing (Tsunoda and Zennyo 2021). For example, Liu et al. (2021) considers a retail platform's information sharing problem in which the platform possesses superior demand information and controls the prediction accuracy level when sharing it to competing sellers. Based on privacy and fairness constraints, they explore different formats for the platform's information sharing, namely asymmetric full/partial sharing and symmetric full/individual sharing. Ha et al. (2022) develops a multistage game-theoretic model to study the impact of retail platforms' information sharing on an upstream manufacturer's encroachment decision and, more generally, the manufacturer's channel choice decision.

This paper contributes to the literature by discussing a new context of digital freight platform's information sharing with firms in supply chains. More specifically, our paper has two differentiating features. First, most of the prior studies address either intra-supply-chain information sharing or vertical information sharing from platform to individual firms. However, digital freight platforms' information sharing combines both platform-to-supply-chain and intra-supply-chain information sharing together. In some sense, our results on the operational effect of digital freight platforms' information sharing generalize the prior result by Ha et al. (2011). Second, only a small proportion of the existing studies consider the platform's strategic prediction accuracy decision. The work of Liu et al. (2021) is an exception, treating the retail platform's prediction accuracy decision as a binary variable of whether to add additional noise to original freight information or not. Unlike Liu et al. (2021), we model the digital freight platform's prediction accuracy decision as a continuous variable. By doing so, we are able to gain deeper insights into how the probability of freight rejection and supply chain competition influence the platform's optimal decision regarding prediction accuracy.

3. The Model

Consider an analytical model consisting of a digital freight platform (simply called "the platform") and a supply chain. In the supply chain, a retailer ("she") purchases goods from a manufacturer ("he") at a wholesale price w. Following the literature (e.g. Ha et al. (2011), Shang et al. (2016), Liu et al. (2021)), we assume that the retailer sells these goods to a Cournot-type market, with a market clearing price of $p = u - q$, where $u > 0$ is the potential market size and q is the retail (or order) quantity. Given the retailer's order quantity q, the manufacturer produces the goods at a cost of $cq + kq^2/2$, where $c > 0$ is the variable cost rate and $k > 0$ is the coefficient of production diseconomy. We note that the manufacturer's production diseconomy (i.e., the marginal production cost increases with volume) is commonly observed in industries such as petroleum refining and auto making (Griffin 1972, Mollick 2004), and is often modeled by a quadratic function in the literature on information sharing (Ha et al. 2011, Shang et al. 2016).

The retailer also requires transportation services to move the procured goods from the manufacturer's site to her own. Following established practices in supply chain logistics (Caplice 2007, Scott et al. 2017, Scott 2015, Caplice 2021), we consider that the retailer works with a contract carrier through a long-term (yearly) contract, under which the retailer pays a fixed contract (freight) rate $r > 0$ for the shipment of the purchased goods. Since we do not consider the negotiation between the retailer and the contracted carrier, the contract rate r is an exogenous parameter in this model. However, the retailer also faces the risk of freight rejection. If freight rejection occurs, the platform helps the retailer find an alternative for-hire carrier to move the goods, with the retailer paying a spot rate S to the for-hire carrier, as well as a commission fee ρ to the platform. Empirical evidence (e.g., Caplice (2007), Scott et al. (2017), Acocella (2022), Caplice (2021)) suggests that a main economic driver for freight rejection is the opportunistic behavior of contracted carriers reserving capacity for spot (freight) rates in a tight freight market. Additionally, the probability $\delta(S)$ of freight rejection is an increasing function of the spot rate S. Therefore, we focus on potential freight rejection in a tight freight market and consider the probability $\delta(S)$ to have a linear form as follows:

$$\delta(S) = \alpha + \ell S, \tag{1}$$

where α is a constant and $\ell > 0$ captures the sensitivity of freight rejection with respect to the spot freight rate. Specifically, the linear function (1) can be viewed as approximation to more complex nonlinear functions (such as logistic functions) used in the empirical studies[2], while also ensuring model tractability. By anticipating possible freight rejection, the retailer's expected freight rate $r_f(S)$, conditioned on the spot rate S, is given by

$$r_f(S) = r(1 - \delta(S)) + (S + \rho)\delta(S). \tag{2}$$

All the players have public knowledge on the spot freight rate $S = s + \epsilon$, where s is the mean of the spot rate and ϵ is random noise with mean zero and variance η. Furthermore, the mean s of the spot

[2] In some empirical papers (such as Scott et al. (2017) and Acocella (2022)), the probability of freight rejection is modeled by logistic function as follows: $L(S) = \frac{1}{1+e^{-(w_0+w_1 S)}}$, where S is spot rate. Then, as shown in the literature (Haldar and Mahadevan 2000), a simple linear mean-value approximation logistic function used is $L(S) \approx L'(s)(S - s) + L(s)$, where s is the mean of S and $L'(\cdot)$ is the first order derivative function.

rate is larger than the contract rate (i.e., $s > r$) in a tight freight market; for example, Aemireddy and Yuan (2019) has shown that the average spot rate is 35% higher than the contracted rate.

The platform has private information Ψ about ϵ. Following the literature on information sharing (Ha et al. 2011, Kurtuluş et al. 2012, Shang et al. 2016, Ha et al. 2017), we assume that the private signal Ψ is an unbiased estimator of ϵ, using a linear-expectation information structure. This information structure includes well-known distributions, such as normal-normal, beta-binomial, and gamma-Poisson. The prediction accuracy of the signal is defined as $a := 1/\mathbb{E}[\mathrm{Var}[\Psi|\theta]]$. The accuracy is known to be proportional to the sample size when Ψ is a sample mean from independent sampling (Ha et al. 2011), and the platform can improve the signal's accuracy by collecting more samples at an acquisition cost wa, where w is the unit cost of collecting data. Let $\mathbb{E}[\epsilon|\Psi]$ denote the posterior mean conditioned on the signal Ψ, which is given by

$$\mathbb{E}[\epsilon|\Psi] = \frac{a}{1/\eta + a}\Psi. \tag{3}$$

Motivated by the practices of digital freight platforms, we consider that the platform has two strategies of information sharing with the supply chain. First, the platform shares its private signal Ψ only with the retailer, i.e., "partial (firm-level) information sharing" (denoted by **P**). Second, the platform not only shares the signal with the retailer, but also allows the retailer to further share it with the manufacturer, i.e., "full (supply-chain-level) information sharing" (denoted by **F**). All the players engage in a multistage game as follows:

1. Initially, the platform selects its information sharing strategy and sets the subscription fee for disclosing the information. Moreover, the manufacturer can induce full information sharing by offering side payments to the retailer and the platform, denoted by T_R and T_P, respectively.
2. After the signal Ψ unveils, the platform determines the brokerage fee ρ for the retailer, and the manufacturer sets the wholesale price w based on the available information.
3. The retailer decides on the order quantity q.

In our model, information sharing agreements by the platform are long-term decisions (such as whether to develop and offer API integration) that are costly to change in the practice of digital freight platforms. The side payment mechanism is widely observed in practice and literature, such as the subscription fees paid by the manufacturer for access to the retailer's (and thus the platform's) private data (Shang et al. 2016, Liu et al. 2021). The brokerage fee and wholesale price are short-term decisions because the platform and the manufacturer can update these decisions over time. Specifically, the platform announces the brokerage fee before the retailer decides the order quantity. This is common practice of digital freight platforms; for example, the full truck alliance platform settles a commission rate ranging from 21 to 52 RMB before shippers decide their volumes (Alliance 2023). This assumption is also used in the literature, enabling retailers to better plan their order quantities considering shipment logistics costs (Chen et al. 2016, 2019). Note that a digital platform does not necessarily observe the manufacturer's wholesale price when deciding the brokerage fee, and the brokerage fee set by the platform is private information to the manufacturer when deciding the wholesale price. As such, we treat the pricing decisions of the platform and the manufacturer as a Nash game.

For ease of exposition, we define the parameter $\pi := u - c - r - \eta\ell - (s-r)(\alpha + s\ell)$, which is decreasing in ℓ. Following the literature (e.g., Li and Zhang (2008), Ha et al. (2011, 2017)), we assume that $\pi > 0$ and that the variance η is small relative to π, ensuring that the equilibrium result will be an interior-point solution for most realizations of demand uncertainty and signals (i.e., with a probability close to one). Finally, we let $\mathbb{R}_+$ denote the non-negative orthant.

4. Single Supply Chain

4.1. Baseline: No Information Sharing

In the baseline setting, the platform does not share any information on the spot rate with the companies in the supply chain, and we solve each player's equilibrium decisions using backward induction as follows. First, given the wholesale price w and the brokerage rate ρ, the retailer's problem is to maximize the expected profit by choosing the order quantity as follows:

$$\max_{q\in\mathbb{R}_+} \left\{\mathbb{E}\left[(u-q-w-r_f(S))q\right]\right\}.$$

Define $\tilde{q}(w,\rho) := \arg\max_{q\in\mathbb{R}_+}\{\mathbb{E}\left[(u-q-w-r_f(S))q\right]\}$ as the retailer's optimal order quantity. Next, we consider the Nash game between the manufacturer's and the platform's pricing decisions. Given the conjecture ρ about the brokerage fee, the manufacturer aims to maximize profit by solving the following problem:

$$\max_{w\in\mathbb{R}_+} \left\{\tilde{q}(w,\rho)(w-c) - \frac{k}{2}\tilde{q}(w,\rho)^2\right\}.$$

Meanwhile, given the conjecture w about the wholesale price, the platform maximizes its revenue from serving the retailer in the case of freight rejection as follows:

$$\max_{\rho\in\mathbb{R}_+} \left\{\mathbb{E}\left[\rho\,\tilde{q}(w,\rho)\,\delta(S)|\Psi\right]\right\}.$$

Let $\tilde{w}(\rho) := \arg\max_{w\in\mathbb{R}_+}\{\tilde{q}(w,\rho)(w-c) - \frac{k}{2}\tilde{q}(w,\rho)^2\}$ and $\tilde{\rho}(w) := \arg\max_{\rho\in\mathbb{R}_+}\{\mathbb{E}\left[\rho\,\tilde{q}(w,\rho)\,\delta(S)|\Psi\right]\}$ be the manufacturer's and the platform's best response functions, respectively. Notably, the platform's best response $\tilde{\rho}(\cdot)$ is independent of the signal Ψ because the retailer's optimal order quantity is independent of it. By jointly considering the manufacturer's and platform's best response functions, we derive their equilibrium prices $w^{\mathbf{N}}$ and $\rho^{\mathbf{N}}$.

By substituting $(w^{\mathbf{N}}, \rho^{\mathbf{N}})$ into the retailer's optimal order quantity, we obtain the supply chain's equilibrium retail quantity, denoted by $q^{\mathbf{N}} := \tilde{q}(w^{\mathbf{N}}, \rho^{\mathbf{N}})$. From $(w^{\mathbf{N}}, \rho^{\mathbf{N}})$, we can also derive the (ex-ante) payoffs for the retailer, the manufacturer, and the platform, denoted by $\Pi_R^{\mathbf{N}}$, $\Pi_M^{\mathbf{N}}$, and $\Pi_P^{\mathbf{N}}$, respectively. This is summarized by the following result:

LEMMA 1. *In a single supply chain, under no information sharing, the supply chain's equilibrium retail quantity is given as follows:*

$$q^{\mathbf{N}} = \frac{\pi}{k+6}. \tag{4}$$

Moreover, the ex-ante payoffs for the retailer, manufacturer, and the platform are given as follows:

$$\Pi_R^{\mathbf{N}} = \frac{\pi^2}{(k+6)^2}, \quad \Pi_M^{\mathbf{N}} = \frac{\pi^2(k+4)}{2(k+6)^2}, \quad \Pi_P^{\mathbf{N}} = \frac{2\pi^2}{(k+6)^2} \tag{5}$$

Proof. See Appendix A.1. □

From Lemma 1 we observe that the supply chain's equilibrium retail quantity and each player's payoff depend only on the prior information about the spot freight rate in the baseline setting. In other words, although the platform has the private signal Ψ, this signal has no effect on any of the players, including the platform, unless it is shared with the companies in the supply chain. This result highlights the necessity for the platform to share its private signal in order to make better use of it.

4.2. Analysis of Information Sharing

We first consider the case of partial information sharing, where the platform shares its private signal Ψ only with the retailer. Conditioned on Ψ, the retailer's problem of maximizing its expected profit is as follows:

$$\max_{q\in\mathbb{R}_+} \left\{\mathbb{E}\left[(u-q-w-r_f(S))\,q|\Psi\right]\right\}.$$

Define $\breve{q}(w,\rho,\Psi) := \arg\max_{q\in\mathbb{R}_+}\{\mathbb{E}\left[(u-q-w-r_f(S))\,q|\Psi\right]\}$ as the platform's optimal order quantity conditional on the signal Ψ. Next, given the conjecture w on the wholesale price, the platform aims to maximize its revenue, conditioned on the signal Ψ, by considering the following problem:

$$\max_{\rho\in\mathbb{R}_+} \left\{\mathbb{E}\left[\rho\,\breve{q}(w,\rho,\Psi)\,\delta(S)|\Psi\right]\right\}.$$

Meanwhile, given the conjecture ρ on the brokerage fee, the manufacturer aims to maximize his expected profit based only on prior information by solving the following problem:

$$\max_{w\in\mathbb{R}_+} \left\{\mathbb{E}\left[\breve{q}(w,\rho,\Psi)(w-c) - \frac{k}{2}\breve{q}(w,\rho,\Psi)^2\right]\right\}.$$

As before, we can derive the platform's and the manufacturer's best response functions, denoted by $\breve{\rho}(w,\Psi) := \arg\max_{\rho\in\mathbb{R}^+}\{\mathbb{E}\left[\rho\,\breve{q}(w,\rho,\Psi)\,\delta(S)|\Psi\right]\}$ and $\breve{w}(\rho) :=$

$\arg\max_{w\in\mathbb{R}_+}\{\mathbb{E}\left[\breve{q}(w,\rho,\Psi)(w-c)-\frac{k}{2}\breve{q}(w,\rho,\Psi)^2\right]\}$, respectively. It should be noted that the platform's response $\breve{\rho}(w,\Psi)$ depends on Ψ, while the manufacturer's response is independent of it. Therefore, we focus on finding the Bayesian Nash equilibrium that simultaneously fulfills their best response functions in the case of partial information sharing.

In the case of full information sharing, the retailer's optimal order quantity and the platform's best response continue to follow $\breve{q}(\cdot)$ and $\breve{\rho}(w,\Psi)$, respectively. However, the manufacturer now observes Ψ and maximizes his conditional expected profit as follows:

$$\max_{w\in\mathbb{R}_+}\left\{\mathbb{E}\Big[\breve{q}(w,\rho,\Psi)(w-c)-\frac{k}{2}\breve{q}(w,\rho,\Psi)^2|\Big]\right\}. \tag{6}$$

Define $\breve{w}'(\rho,\Psi):=\arg\max_{w\in\mathbb{R}_+}\{\mathbb{E}\left[\breve{q}(w,\rho,\Psi)(w-c)-\frac{k}{2}\breve{q}(w,\rho,\Psi)^2\right]|\Psi\}$ as the manufacturer's best response in the case of full information sharing. We then can find the Nash equilibrium that jointly satisfies $\breve{\rho}(w,\Psi)$ and $\breve{w}'(\rho,\Psi)$.

By substituting these equilibrium wholesales prices and brokerage fees into the retailer's optimal retail quantity $\breve{q}(\cdot)$, we obtain the supply chain's equilibrium retail quantity, denoted by $q^{\mathbf{Y}}$, under the platform's information sharing arrangement $\mathbf{Y}\in\{\mathbf{P},\mathbf{F}\}$. We also let $\Pi_R^{\mathbf{Y}}$, $\Pi_M^{\mathbf{Y}}$, and $\Pi_P^{\mathbf{P}}$ denote the payoffs for the retailer, the manufacturer, and the platform, respectively. By further defining $v_1:=\mathbb{E}\left[\mathbb{E}\left[\epsilon|\Psi\right]^2\right]=\frac{\eta^2}{\eta+1/a}$ and $v_2:=\mathbb{E}\left[\mathbb{E}\left[\epsilon^2|\Psi\right]^2\right]-\eta^2=\frac{2\eta^4}{(\eta+1/a)^2}$, we have the following result:

PROPOSITION 1. *In a single supply chain, under either partial or full information sharing, the supply chain's equilibrium retail quantities are given as follows:*

$$\begin{aligned} q^{\mathbf{P}} &= q^{\mathbf{N}}+\frac{\ell(\eta-\mathbb{E}\left[\epsilon|\Psi\right](2s-r)-\mathbb{E}\left[\epsilon^2|\Psi\right])-\alpha\mathbb{E}\left[\epsilon|\Psi\right]}{4},\\ q^{\mathbf{F}} &= q^{\mathbf{N}}+\frac{\ell(\eta-\mathbb{E}\left[\epsilon|\Psi\right](2s-r)-\mathbb{E}\left[\epsilon^2|\Psi\right])-\alpha\mathbb{E}\left[\epsilon|\Psi\right]}{k+6}. \end{aligned} \tag{7}$$

Moreover, all players' payoffs are given as follows:

$$\begin{aligned} \Pi_R^{\mathbf{P}} &= \Pi_R^{\mathbf{N}}+\frac{(\alpha+(2s-r)\ell)^2v_1+\ell^2v_2}{16}, & \Pi_R^{\mathbf{F}} &= \Pi_R^{\mathbf{N}}+\frac{(\alpha+(2s-r)\ell)^2v_1+\ell^2v_2}{(k+6)^2},\\ \Pi_M^{\mathbf{P}} &= \Pi_M^{\mathbf{N}}-k\frac{(\alpha+(2s-r)\ell)^2v_1+\ell^2v_2}{32}, & \Pi_M^{\mathbf{F}} &= \Pi_M^{\mathbf{N}}+\frac{(k+4)((\alpha+(2s-r)\ell)^2v_1+\ell^2v_2)}{2(k+6)^2},\\ \Pi_P^{\mathbf{P}} &= \Pi_P^{\mathbf{N}}+\frac{(\alpha+(2s-r)\ell)^2v_1+\ell^2v_2}{8}, & \Pi_P^{\mathbf{F}} &= \Pi_P^{\mathbf{N}}+\frac{2((\alpha+(2s-r)\ell)^2v_1+\ell^2v_2)}{(k+6)^2}. \end{aligned} \tag{8}$$

Proof. See Appendix A.2. □

From (7) in Proposition 1, we observe that the supply chain's equilibrium retail quantity under either partial or full information sharing is expressed as the sum of the retail quantity $q^{\mathbf{N}}$ in the baseline setting and further adjustments made by the supply chain based on the private signal Ψ (i.e., the terms $\frac{\ell(\eta-\mathbb{E}[\epsilon|\Psi](2s-r)-\mathbb{E}\left[\epsilon^2|\Psi\right])-\alpha\mathbb{E}[\epsilon|\Psi]}{4}$ and $\frac{\ell(\eta-\mathbb{E}[\epsilon|\Psi](2s-r)-\mathbb{E}\left[\epsilon^2|\Psi\right])-\alpha\mathbb{E}[\epsilon|\Psi]}{k+6}$ in $q^{\mathbf{P}}$ and $q^{\mathbf{F}}$, respectively). Similarly, all players' payoffs are given by the combination of their payoffs $\Pi_R^{\mathbf{N}}$, $\Pi_M^{\mathbf{N}}$, and

$\Pi_P^{\mathbf{P}}$ in the baseline setting and the payoff surplus (or shortfall) caused by the adjustments made due to the private signal Ψ. In particular, partial information sharing results in a surplus shortfall for the manufacturer, captured by the term $-k\frac{(\alpha+(2s-r)\ell)^2 v_1+\ell^2 v_2}{32}$. This shortfall occurs because the manufacturer cannot effectively respond to the retailer's adjustment in her retail quantity without observing the private signal Ψ, leading to increased production costs due to production diseconomy.

Moreover, based on the payoffs shown in Proposition 1, we can quantify the effect of the platform's information sharing strategies $\mathbf{Y} \in \{\mathbf{P}, \mathbf{F}\}$ on every player relative to the benchmark of no information sharing by examining the quantities $\Pi_R^{\mathbf{Y}} - \Pi_R^{\mathbf{N}}$, $\Pi_M^{\mathbf{Y}} - \Pi_M^{\mathbf{N}}$, and $\Pi_P^{\mathbf{Y}} - \Pi_P^{\mathbf{N}}$. We can also compare the effects of partial/full information sharing on every player by examining $\Pi_R^{\mathbf{F}} - \Pi_R^{\mathbf{P}}$, $\Pi_M^{\mathbf{F}} - \Pi_M^{\mathbf{P}}$, and $\Pi_P^{\mathbf{F}} - \Pi_P^{\mathbf{P}}$.

PROPOSITION 2. *In a single supply chain, information sharing by the platform results in the following:*

(a) Partial information sharing benefits the retailer and the platform (i.e., $\Pi_R^{\mathbf{P}} > \Pi_R^{\mathbf{N}}$ and $\Pi_P^{\mathbf{P}} > \Pi_P^{\mathbf{N}}$), but hurts the manufacturer (i.e., $\Pi_M^{\mathbf{P}} < \Pi_M^{\mathbf{N}}$).

(b) Full information sharing benefits the retailer, the manufacturer, and the platform (i.e., $\Pi_R^{\mathbf{F}} > \Pi_R^{\mathbf{N}}$, $\Pi_M^{\mathbf{F}} > \Pi_M^{\mathbf{N}}$ and $\Pi_P^{\mathbf{F}} > \Pi_P^{\mathbf{N}}$).

(c) Compared to partial information sharing, full information sharing generates more value for the manufacturer (i.e., $\Pi_M^{\mathbf{F}} - \Pi_M^{\mathbf{N}} > \Pi_M^{\mathbf{P}} - \Pi_M^{\mathbf{N}}$) but generates less value for the retailer and the platform (i.e., $\Pi_R^{\mathbf{F}} - \Pi_R^{\mathbf{N}} < \Pi_R^{\mathbf{P}} - \Pi_R^{\mathbf{N}}$ and $\Pi_P^{\mathbf{F}} - \Pi_P^{\mathbf{N}} < \Pi_P^{\mathbf{P}} - \Pi_P^{\mathbf{N}}$).

Proof. See Appendix A.3. □

Parts (a) and (b) of Proposition 2 can be interpreted as follows. On the one hand, both partial and full information sharing benefit the retailer and the platform (that is, $\Pi_R^{\mathbf{Y}} > \Pi_R^{\mathbf{N}}$ and $\Pi_P^{\mathbf{Y}} < \Pi_P^{\mathbf{N}}$ for $\mathbf{Y} \in \{\mathbf{P}, \mathbf{F}\}$) because information sharing allows the retailer to better adjust her order quantity and allows the platform to leverage the business value of its private information. On the other hand, only full information sharing benefits the manufacturer because it enables him to adjust the wholesale price based on Ψ. Part (c) of Proposition 2 further compares the values of partial and full information sharing to the retailer, the manufacturer, and the platform, and shows that full information sharing generates less value for the retailer and the platform. This outcome is due to the well-known *double marginalization effect* (DME) in supply chains. That is, the manufacturer's adjustment of the wholesale price works against the retailer's and the platform's respective adjustments to the order quantity and brokerage fee.

It is worth mentioning that the DME of information sharing on downstream retailers has been addressed by the literature (Ha et al. 2011, Shang et al. 2016). However, Proposition 2 shows that information sharing by a digital freight platform also leads to a DME on the platform itself; this finding is novel and extends the existing literature. The primary implications of Proposition 2 are two-fold. First, the baseline strategy of no information sharing is dominated by the platform's information sharing strategies (either partial or full), which explains the economic incentives for information sharing by digital freight platforms in practice. Second, the manufacturer needs to induce full information sharing by offering side payments T_R (no less than $|\Pi_R^{\mathbf{F}} - \Pi_R^{\mathbf{P}}|$) and T_P (no less than $|\Pi_P^{\mathbf{F}} - \Pi_P^{\mathbf{P}}|$) to the retailer and the platform, respectively, to compensate for their losses from sharing private data. With these side payments, the manufacturer's net value under full information sharing is given by

$$\Pi_M^{\mathbf{F}} - \Pi_M^{\mathbf{P}} - T_R - T_P. \tag{9}$$

Thus, full information sharing is possible only when the manufacturer's net value is nonnegative. Based on this observation, we obtain the following result.

PROPOSITION 3. *In a single supply chain, we have the following:*

(a) When the manufacturer's production diseconomy is sufficiently large, i.e., $k > 2(2\sqrt{2} - 1)$*, full information sharing is induced by side payments from the manufacturer to the retailer and the platform; otherwise, partial information sharing is adopted.*

(b) Under possible side payments, the platform's gross payoff under either partial or full information sharing is given by

$$\frac{2\pi^2}{(k+6)^2} + \frac{(\alpha + (2s - r)\ell)^2 v_1 + \ell^2 v_2}{8}$$

Proof. See Appendix A.4. □

Part (a) of Proposition 3 highlights that the manufacturer's production diseconomy is a necessary condition for full information sharing. Specifically, full information sharing is induced when the upstream production diseconomy is sufficiently large. This result can be explained as follows. As the manufacturer's production diseconomy becomes large, i.e., as k increases, the manufacturer can reduce more production costs under full information sharing compared to partial information sharing, enabling the manufacturer to cover the side payments to the retailer and the platform. Part (b) shows the platform's gross payoff, accounting for possible side payments. Specifically, the terms $\frac{2\pi^2}{(k+6)^2}$ and $\frac{(\alpha+(2s-r)\ell)^2 v_1 + \ell^2 v_2}{8}$ arise from the public prior information and the platform's private information, respectively.

The literature (e.g., Ha et al. (2011), Shang et al. (2016)) has examined the economic incentives for downstream companies to share information with upstream companies in a supply chain, demonstrating that side payments between firms are effective in inducing information sharing.

Propositions 2 and 3 extend the literature by analyzing the economic incentives for a platform to share information with companies in a supply chain. Specifically, a platform also needs to be incentivized to share information with upstream firms, facilitated through side payments from these firms. In practice, such side payments can take the form of information subscription fees paid by upstream firms to the platform to allow API integration. This arrangement is feasible only when the upstream production diseconomy is sufficiently large.

Next, we consider the platform's problem of maximizing its net payoff, i.e., the platform's gross payoff minus the information cost wa, by optimizing over the accuracy a as follows:

$$\max_{a\in\mathbb{R}_+}\left\{\frac{2\pi^2}{(k+6)^2}+\frac{(\alpha+(2s-r)\ell)^2 v_1(a)+\ell^2 v_2(a)}{8}-w\,a\right\}. \tag{10}$$

The term $\frac{(\alpha+(2s-r)\ell)^2 v_1(a)+\ell^2 v_2(a)}{8}$ in (10) represents the platform's payoff surplus due to sharing its private signal, which increases as the prediction accuracy a increases. A key parameter in the objective function (10) is the sensitivity coefficient ℓ. As the coefficient ℓ increases, meaning that the retailer becomes more sensitive to freight rejection risks, the term $\frac{2\pi^2}{(k+6)^2}$ (which represents the platform's payoff generated by prior information) decreases because the parameter π is decreasing in ℓ, while the term $\frac{(\alpha+(2s-r)\ell)^2 v_1(a)+\ell^2 v_2(a)}{8}$ is increasing in ℓ. Furthermore, we consider the following inequality to ensure that the platform's optimal prediction accuracy is positive:

$$w\le\frac{\eta^2(\alpha+(2s-r)\ell)^2}{8}. \tag{11}$$

Proposition 4. *For single supply chain, the platform's optimal prediction accuracy a^* has the following properties:*

(a) Under (11), the platform's objective function (10) is quasi-concave, and the optimal prediction accuracy a^* is unique.

(b) The optimal prediction accuracy a^* increases as the sensitivity coefficient ℓ of freight rejection increases.

(c) Under the optimal prediction accuracy a^*, the retailer's and platform's net payoffs initially decrease and then increase, whereas the manufacturer's net payoff decreases as the sensitivity coefficient ℓ of freight rejection increases.

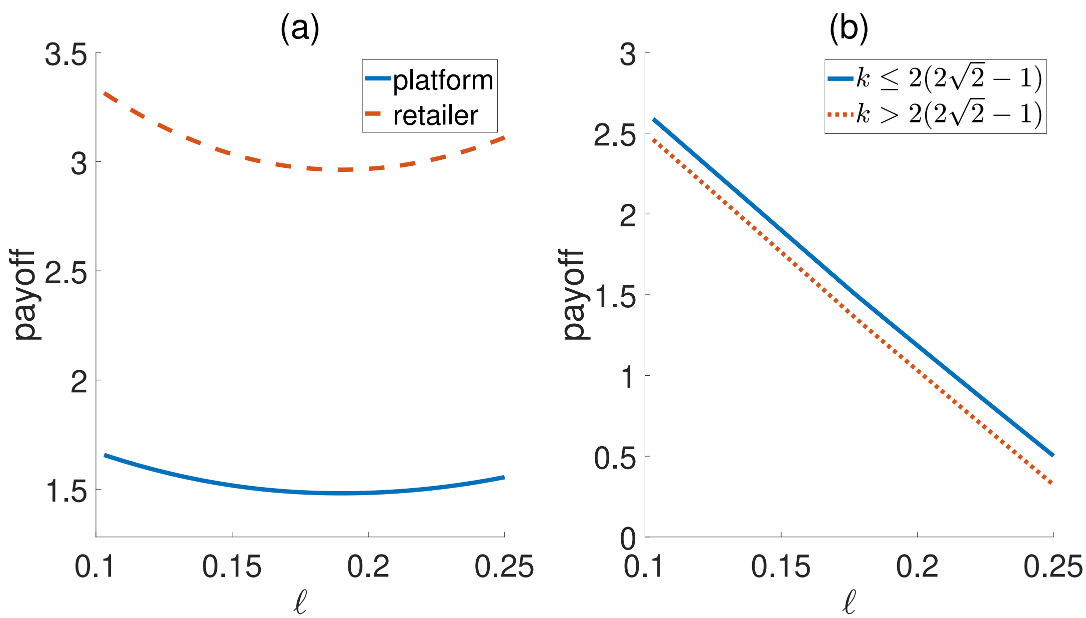
Proof. See Appendix B.3. □

Part (a) of Proposition 4 characterizes the quasi-concavity of the platform's objective function (10), which ensures the uniqueness of the platform's optimal prediction accuracy. Part (b) presents the comparative statics of the platform's optimal prediction accuracy a^* with respect to the sensitivity coefficient ℓ of freight rejection. Specifically, as ℓ increases, it becomes optimal for the platform to improve its private prediction accuracy because the platform exploits more business value from a more accurate signal by increasing the responsiveness of the supply chain's equilibrium retail quantity. Part (c) characterizes the behavior of each players' payoff (considering the possible side payments) under the platform's optimal prediction accuracy as ℓ increases; see Figure 1. Interestingly, we find that the retailer's payoff initially decreases and then increases with ℓ, indicating that a higher sensitivity to freight rejection can benefit the retailer. This result contradicts the conventional understanding of the negative impact of freight rejection risks on shippers, as discussed in the literature (Scott 2015, Caplice 2021). This finding arises from the fact that, under the platform's information sharing, the retailer's payoff surplus generated by the private signal (i.e., $\frac{(\alpha+(2s-r)\ell)^2 v_1(a^*)+\ell^2 v_2(a^*)}{16}$) actually increases with ℓ. Similarly, the platform's payoff also initially decreases and then increases with ℓ. However, the manufacturer's payoff always decreases as the sensitivity coefficient ℓ increases, regardless of whether the manufacturer offers side payments to induce information sharing.

Proposition 4 is closely related to ongoing debates in the literature on how to manage freight rejection risks (e.g., Scott et al. (2017), Acocella (2022)). Specifically, a few solutions have been proposed to reduce the sensitivity coefficient ℓ of freight rejection, such as through flexible freight contracts. This paper complements the existing literature by offering a new solution—improving shippers' responsiveness to freight rejection through information sharing by digital freight platforms. The non-monotonic behavior of the retailer's net payoff also reveals interactions between existing solutions in the literature and our proposed solution. Notably, we find that existing approaches aimed at reducing ℓ may harm the retailer under the platform's information sharing arrangement. For example, in Figure 1(a), we see that if the original value of ℓ is 0.25, then the retailer experiences a decrease in her net payoff when ℓ is reduced to 0.2. This result implies that information sharing by the platform may lead to a negative spillover effect on the effectiveness of other supply chain solutions for addressing freight rejection. As such, firms in supply chains should be cautious about the mixed use of different solutions for freight rejection.

We also explore an extension of the main model in Appendix C by considering the probability of freight rejection as dependent on the retailer's order quantity. Empirical studies (e.g., Scott et al. (2017), Acocella (2022)) have shown that a carrier's probability of freight rejection increases as a shipper's cargo volume increases, due to the added operational complexity associated with larger cargo volumes. Motivated by this observation, we assume that the probability of freight rejection decreases as the retailer's order quantity decreases. Our analysis shows that the main insights continue to hold when the sensitivity of the probability of freight rejection is not too high.

Figure 1 **The behavior of each player's payoff for different values $\ell \in (0.1, 0.25)$, where $u = 12, s = 5, c = 0, \alpha = 0.1, \eta = 2, k = 3, w = 0.05, r = 2$. Figure (a) depicts the retailer' and the platform's payoffs. Figure (b) visualizes the manufacturer's payoff, with possible side payments depending on the coefficient k of production diseconomy.**



5. Competing Supply Chains

In this section, we consider information sharing by a digital freight platform in a competitive setting. Following the literature (Ha et al. 2011, 2017, Liu et al. 2021), we extend the main model to consider two competing supply chains. Each supply chain $i \in 1, 2$ consists of a retailer i and a manufacturer i, and the two retailers sell substitute products to customers in a Cournot competition. The market clearing price p_i for retailer i is given by:

$$p_i = u - q_i - \gamma q_j,$$

where u is a constant, $\gamma \in (0, 1)$ is the coefficient of competition intensity, and (q_i, q_j) are the retail quantities of retailer i and retailer j, respectively.

The sequence of events in this generalized model with competition is as follows. First, the platform selects the accuracy a of the private signal Ψ and decides the information arrangement $\mathbf{Y}_i \in \{\mathbf{N}, \mathbf{P}, \mathbf{F}\}$ for each supply chain $i = 1, 2$. Second, the manufacturer i in each supply chain sets the wholesale price w_i, and the platform announces the brokerage fee ρ_i for retailer i through a Nash game. Finally, each retailer i determines the order quantity q_i. Our consideration of the platform charging heterogeneous brokerage fees for different retailers is motivated by real-world practices—namely, a digital freight platform negotiates privately with different shippers to settle individual brokerage fees in order to maximize revenue. Moreover, the brokerage fee ρ_i for retailer

i is not observable for retailer j, and the platform is not allowed to disclose ρ_i to retailer j due to privacy restrictions (Coughlan and Wernerfelt 1989, Liu et al. 2021).

For analytical convenience, we assume that competing supply chains have symmetric costs. Specifically, both retailers have the same contracted freight rate r and the same probability $\delta(S)$ of freight rejection. Furthermore, both manufacturers have identical production costs $cq+kq^2/2$.

Next, we analyze the equilibrium retail quantities for competing supply chains. Due to the aforementioned privacy restrictions, the retailer i and the manufacturer i in a focal supply chain i do not know rival supply chain j's retail quantity when making their own decisions. Following the literature (e.g., Ha et al. (2011), Shang et al. (2016), Ha et al. (2017)), we assume that retailer i and manufacturer i form a common conjecture q_j about the retail quantity of the rival supply chain j'. Following the analysis of single supply chain, we can derive supply chain i's best (retail quantity) response function $\hat{q}_i^{\mathbf{Y}_i}(q_j)$ given its information arrangement $\mathbf{Y}_i \in \{\mathbf{N},\mathbf{P},\mathbf{F}\}$. Similarly, by assuming that retailer j and manufacturer j have a common conjecture q_i about focal supply chain i's retail quantity, we derive rival supply chain j's response function $\hat{q}_j^{\mathbf{Y}_j}(q_i)$ given its information arrangement $\mathbf{Y}_j \in \{\mathbf{N},\mathbf{P},\mathbf{F}\}$. We then determine the Bayesian Nash equilibrium (BNE) retail quantities that satisfy both response functions $\hat{q}_i^{\mathbf{Y}_i}(q_j)$ and $\hat{q}_j^{\mathbf{Y}_j}(q_i)\}$. Denoting the equilibrium retail quantities by $q_i^{\mathbf{Y}_i,\mathbf{Y}_j}$ and $q_j^{\mathbf{Y}_j,\mathbf{Y}_i}$, we have the following result.

PROPOSITION 5. *In competing supply chains, there is a unique pair of Bayesian Nash equilibrium retail quantities given as follows:*

$$\begin{aligned} q_i^{\mathbf{Y}_i,\mathbf{Y}_j} &= \frac{\pi}{\gamma+k+6} + \phi_{i_0}^{\mathbf{Y}_i,\mathbf{Y}_j}\mathbb{E}\left[\epsilon^2\right] + \phi_{i_1}^{\mathbf{Y}_i,\mathbf{Y}_j}\mathbb{E}\left[\epsilon|\Psi\right] + \phi_{i_2}^{\mathbf{Y}_i,\mathbf{Y}_j}\mathbb{E}\left[\epsilon^2|\Psi\right], \\ q_j^{\mathbf{Y}_j,\mathbf{Y}_i} &= \frac{\pi}{\gamma+k+6} + \phi_{j_0}^{\mathbf{Y}_j,\mathbf{Y}_i}\mathbb{E}\left[\epsilon^2\right] + \phi_{j_1}^{\mathbf{Y}_j,\mathbf{Y}_i}\mathbb{E}\left[\epsilon|\Psi\right] + \phi_{j_2}^{\mathbf{Y}_j,\mathbf{Y}_i}\mathbb{E}\left[\epsilon^2|\Psi\right], \end{aligned}$$

where the coefficients $\phi_i^{\mathbf{Y}_i,\mathbf{Y}_j} = \left(\phi_{i_0}^{\mathbf{Y}_i,\mathbf{Y}_j}, \phi_{i_1}^{\mathbf{Y}_i,\mathbf{Y}_j}, \phi_{i_2}^{\mathbf{Y}_i,\mathbf{Y}_j}\right)$ *and* $\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i} = \left(\phi_{j_0}^{\mathbf{Y}_j,\mathbf{Y}_i}, \phi_{j_1}^{\mathbf{Y}_j,\mathbf{Y}_i}, \phi_{j_2}^{\mathbf{Y}_j,\mathbf{Y}_i}\right)$ *are shown in Table 1.*

Proof. See Appendix B.1. □

Proposition 5 shows that each supply chain i's equilibrium retail quantity is a linear combination of the terms $\mathbb{E}[\epsilon^2]$, $\mathbb{E}[\epsilon|\Psi]$, and $\mathbb{E}[\epsilon^2|\Psi]$ conditioned on public prior information and private posterior information. The weights $\phi_{i_0}^{\mathbf{Y}_i,\mathbf{Y}_j}$, $\phi_{i_1}^{\mathbf{Y}_i,\mathbf{Y}_j}$, and $\phi_{i_2}^{\mathbf{Y}_i,\mathbf{Y}_j}$ represent the response factors in the supply chain i's equilibrium retail quantity for each of the expected noisy terms.

Based on Proposition 5, we derive the ex-ante payoffs for all players. Specifically, given rival supply chain j's retail quantity $q_j^{\mathbf{Y}_j,\mathbf{Y}_i}$, we rewrite retailer i's market clearing price as follows:

$$p_i = (u - \gamma\, q_j^{\mathbf{Y}_j,\mathbf{Y}_i}) - q_i = \hat{u}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i}) - q_i,$$

Table 1 The coefficients in competing supply chains' Bayesian Nash equilibrium retail quantities

$(\mathbf{Y}_i,\mathbf{Y}_j)$	$\phi_{i_0}^{\mathbf{Y}_i,\mathbf{Y}_j}$	$\varphi_{i_1}^{\mathbf{Y}_i,\mathbf{Y}_j}$	$\phi_{i_2}^{\mathbf{Y}_i,\mathbf{Y}_j}$	$\Phi_{j_0}^{\mathbf{Y}_j,\mathbf{Y}_i}$	$\varphi_{j_1}^{\mathbf{Y}_j,\mathbf{Y}_i}$	$\phi_{j_2}^{\mathbf{Y}_j,\mathbf{Y}_i}$
$(\mathbf{N},\mathbf{N})$	0	0	0	0	0	0
$(\mathbf{P},\mathbf{N})$	$\frac{\ell}{4}$	$\frac{(r-2s)\ell-\alpha}{4}$	$-\frac{\ell}{4}$	0	0	0
$(\mathbf{F},\mathbf{N})$	$\frac{\ell}{k+6}$	$\frac{(r-2s)\ell-\alpha}{k+6}$	$-\frac{\ell}{k+6}$	0	0	0
$(\mathbf{N},\mathbf{P})$	0	0	0	$\frac{\ell}{4}$	$\frac{(r-2s)\ell-\alpha}{4}$	$-\frac{\ell}{4}$
$(\mathbf{P},\mathbf{P})$	$\frac{\ell}{\gamma+4}$	$\frac{(r-2s)\ell-\alpha}{\gamma+4}$	$-\frac{\ell}{\gamma+4}$	$\frac{\ell}{\gamma+4}$	$\frac{(r-2s)\ell-\alpha}{\gamma+4}$	$-\frac{\ell}{\gamma+4}$
$(\mathbf{F},\mathbf{P})$	$\frac{(\gamma-4)\ell}{\gamma^2-4(k+6)}$	$\frac{(\gamma-4)((r-2s)\ell-\alpha)}{\gamma^2-4(k+6)}$	$\frac{(\gamma-4)\ell}{24-\gamma^2+4k}$	$\frac{\ell(k+6-\gamma)}{24-\gamma^2+4k}$	$\frac{(k+6-\gamma)((r-2s)\ell-\alpha)}{24-\gamma^2+4k}$	$\frac{\ell(\gamma-k-6)}{24-\gamma^2+4k}$
$(\mathbf{N},\mathbf{F})$	0	0	0	$\frac{\ell}{k+6}$	$\frac{(r-2s)\ell-\alpha}{k+6}$	$-\frac{\ell}{k+6}$
$(\mathbf{P},\mathbf{F})$	$\frac{\ell(k+6-\gamma)}{24-\gamma^2+4k}$	$\frac{(k+6-\gamma)((r-2s)\ell-\alpha)}{24-\gamma^2+4k}$	$\frac{\ell(\gamma-k-6)}{24-\gamma^2+4k}$	$\frac{(\gamma-4)\ell}{\gamma^2-4(k+6)}$	$\frac{(\gamma-4)((r-2s)\ell-\alpha)}{\gamma^2-4(k+6)}$	$\frac{(\gamma-4)\ell}{24-\gamma^2+4k}$
$(\mathbf{F},\mathbf{F})$	$\frac{\ell}{\gamma+k+6}$	$\frac{(r-2s)\ell-\alpha}{\gamma+k+6}$	$-\frac{\ell}{\gamma+k+6}$	$\frac{\ell}{\gamma+k+6}$	$\frac{(r-2s)\ell-\alpha}{\gamma+k+6}$	$-\frac{\ell}{\gamma+k+6}$

where $\hat{u}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i}) = u - \gamma(\frac{\pi}{\gamma+k+6} + \phi_{j_0}^{\mathbf{Y}_j,\mathbf{Y}_i}\mathbb{E}[\epsilon^2] + \phi_{j_1}^{\mathbf{Y}_j,\mathbf{Y}_i}\mathbb{E}[\epsilon|\Psi] + \phi_{j_2}^{\mathbf{Y}_j,\mathbf{Y}_i}\mathbb{E}[\epsilon^2|\Psi])$ represents supply chain i's potential market size, which is a function of the coefficients $\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i}$ capturing rival supply chain j's competitive response. Following the analysis of single supply chain, we can derive retailer i's and manufacturer i's payoffs, denoted by $\Pi_{R_i}^{\mathbf{Y}_i}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i})$ and $\Pi_{M_i}^{\mathbf{Y}_i}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i})$, respectively, as well as the platform's payoff for serving retailer i, denoted by $\Pi^{\mathbf{Y}_i}P_i(\phi^{\mathbf{Y}_j,\mathbf{Y}_i}j)$. A summary of the expressions for $\Pi_{R_i}^{\mathbf{Y}_i}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i})$, $\Pi_{M_i}^{\mathbf{Y}_i}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i})$, and $\Pi_{P_i}^{\mathbf{Y}_i}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i})$ is provided in Appendix B.2.

Similar to the single supply chain, we next examine the effect of information sharing on a focal supply chain i. Specifically, for $\mathbf{Y}_i \in \{\mathbf{P},\mathbf{F}\}$, we quantify the the effect of information sharing on retailer i and manufacturer i by using their payoff differences:

$$\Pi_{R_i}^{\mathbf{Y}_i}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{Y}_i}) - \Pi_{R_i}^{\mathbf{N}}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{N}}), \quad \Pi_{M_i}^{\mathbf{Y}_i}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{Y}_i}) - \Pi_{M_i}^{\mathbf{N}}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{N}}). \tag{12}$$

We can also assess the effect of information sharing with focal supply chain i on the platform as follows:

$$\left[\Pi_{P_i}^{\mathbf{Y}_i}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{Y}_i}) + \Pi_{P_j}^{\mathbf{Y}_j}(\boldsymbol{\phi}_i^{\mathbf{Y}_i,\mathbf{Y}_j})\right] - \left[\Pi_{P_i}^{\mathbf{N}}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{N}}) + \Pi_{P_j}^{\mathbf{Y}_j}(\boldsymbol{\phi}_i^{\mathbf{N},\mathbf{Y}_j})\right], \tag{13}$$

where the term $\left[\Pi_{P_i}^{\mathbf{Y}_i}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{Y}_i}) + \Pi_{P_j}^{\mathbf{Y}_j}(\boldsymbol{\phi}_i^{\mathbf{Y}_i,\mathbf{Y}_j})\right]$ represents the platform's payoff from serving both retailers when sharing information with supply chain i, i.e., $\mathbf{Y}_i \in \{\mathbf{F},\mathbf{P}\}$, and the term $\left[\Pi_{P_i}^{\mathbf{N}}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{N}}) + \Pi_{P_j}^{\mathbf{Y}_j}(\boldsymbol{\phi}_i^{\mathbf{N},\mathbf{Y}_j})\right]$ represents its payoff without sharing information to supply chain i, i.e., $\mathbf{Y}_i = \mathbf{N}$.

PROPOSITION 6. *Compared to the baseline of no information sharing, we have the following:*

(a) Partial information sharing always benefits retailer i and the platform, but hurts manufacturer i regardless of rival supply chain j's information sharing arrangement.

(b) Full information sharing always benefits retailer i and manufacturer i, but hurts the platform if and only if rival supply chain j's information arrangement is partial information sharing and the upstream production diseconomy is sufficiently large, i.e., $k > \frac{\gamma^3+4\gamma^2-64\gamma+64}{8\gamma}$.

Proof. See Appendix B.4. □

Part (a) of Proposition 6 shows that the retailers and the platform are always incentivized to adopt partial information sharing. This is because they obtain a payoff surplus by enhancing the responsiveness of their equilibrium decisions to freight rejection. Part (b) of Proposition 6 shows that full information sharing can hurt the platform if and only if rival supply chain j's information arrangement is partial information sharing and the upstream production diseconomy is sufficiently large, i.e., $k \geq \frac{\gamma^3+4\gamma^2-80\gamma+64}{8\gamma}$. This occurs because the DME reduces the platform's revenue from retailer j, i.e., $\Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{FP}}_i) - \Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{NP}}_i) < 0$. Notably, this result differs from the previous finding in the single supply chain setting, as shown in Proposition 2(b). An important implication of Proposition 6 is that no information sharing is dominated by partial information sharing for each of the competing supply chains. Hence, it is safe to ignore the baseline strategy in the following analysis.

Next, we explore the effect of full information sharing relative to partial information sharing. Specifically, given rival supply chain j's information sharing arrangement $\mathbf{Y}_j \in \{\mathbf{P}, \mathbf{F}\}$, we assess the effect of full information sharing on retailer i and manufacturer i as follows:

$$\Pi^{\mathbf{F}}_{R_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{F}}_j) - \Pi^{\mathbf{P}}_{R_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{P}}_j), \quad \Pi^{\mathbf{F}}_{M_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{F}}_j) - \Pi^{\mathbf{P}}_{M_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{P}}_j).$$

Moreover, full information sharing by the platform to the focal supply chain i also affects its own payoff as follows:

$$\begin{aligned} &\left[\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{F}}_j) + \Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}^{\mathbf{F},\mathbf{Y}_j}_i)\right] - \left[\Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{P}}_j) + \Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}^{\mathbf{P},\mathbf{Y}_j}_i)\right] \\ =& \underbrace{\left[\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{F}}_j) - \Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{P}}_j)\right]}_{\text{Direct effect}} + \underbrace{\left[\Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}^{\mathbf{F},\mathbf{Y}_j}_i) - \Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}^{\mathbf{P},\mathbf{Y}_j}_i)\right]}_{\text{Side effect}}, \end{aligned}$$

where the term $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{F}}_j) - \Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{P}}_j)$ represents the direct effect of full information sharing to focal supply chain i on the platform's revenue from serving retailer i, and the term $\Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}^{\mathbf{F},\mathbf{Y}_j}_i) - \Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}^{\mathbf{P},\mathbf{Y}_j}_i)$ represents the side effect of full information sharing on the platform's revenue from serving retailer j.

Proposition 7. *In competing supply chains, relative to partial information sharing, we have the following:*

(a) Full information sharing in supply chain i generates more value for manufacturer i (i.e., $\Pi^{\mathbf{F}}_{M_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{F}}_j) > \Pi^{\mathbf{P}}_{M_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{P}}_j)$), but generates less value for retailer i (i.e., $\Pi^{\mathbf{F}}_{R_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{F}}_j) < \Pi^{\mathbf{P}}_{R_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{P}}_j)$) , regardless of rival supply chain j's information sharing arrangement (i.e., $\mathbf{Y}_j \in \{\mathbf{P}, \mathbf{F}\}$).

(b) The direct effect of full information sharing generates less value for the platform (i.e., $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{F}}) < \Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{P}})$), the side effect generates more value for the platform (i.e., $\Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}_i^{\mathbf{F},\mathbf{Y}_j}) > Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}_i^{\mathbf{P},\mathbf{Y}_j})$), and the overall effect generates less value for the platform (i.e., $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{F}}) + \Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}_i^{\mathbf{F},\mathbf{Y}_j}] < \Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}_j^{\mathbf{Y}_j,\mathbf{P}}) + \Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}_i^{\mathbf{P},\mathbf{Y}_j})$), regardless of rival supply chain j's information sharing arrangement (i.e., $\mathbf{Y}_j \in \{\mathbf{P},\mathbf{F}\}$).

(c) Full information sharing is induced in supply chain i under manufacturer i's side payments T_{R_i} and T_{P_i} to retailer i and the platform, respectively. When rival supply chain j has partial information sharing (resp., full information sharing), full information sharing will be adopted in the focal supply chain i if and only if $k > \kappa^{\mathbf{P}}$ (resp., $k > \kappa^{\mathbf{F}}$), where $\kappa^{\mathbf{P}}$ and $\kappa^{\mathbf{F}}$ are two constants.

Proof. See Appendix B.5. □

From Proposition 7(a) we find that the effect of full information sharing on retailer i and manufacturer i is similar to the result given in Proposition 2. It is straightforward to verify that the full information sharing with the focal supply chain i makes its own demand less variable (i.e., $\mathrm{Var}\,[\hat{q}_i^{\mathbf{P},\mathbf{Y}_j}] \geq \mathrm{Var}\,[\hat{q}_i^{\mathbf{F},\mathbf{Y}_j}]$), resulting in a negative direct effect on the platform. At the same time, it makes rival supply chain j's equilibrium retail demand more variable (i.e., $\mathrm{Var}\,[\hat{q}_j^{\mathbf{Y}_j,\mathbf{F}}] \geq \mathrm{Var}\,[\hat{q}_j^{\mathbf{Y}_j,\mathbf{P}}]$), resulting in a positive side effect on the platform. Moreover, as shown in Proposition 7(b), the negative direct effect on the platform outweighs the positive side effect, which means full information sharing is ultimately less valuable to the platform relative to partial information sharing. Furthermore, from Proposition 7(a) and (b), we conclude that manufacturer i must provide side payments T_{R_i} and T_{P_i} to retailer i and the platform, respectively, to induce full information sharing. With these possible side payments, manufacturer i's net value under full information sharing is positive only when his production diseconomoy is sufficiently large, i.e., $k > \kappa^{\mathbf{Y}_j}, \mathbf{Y}_j \in \{\mathbf{P},\mathbf{F}\}$. The definitions of $\kappa^{\mathbf{P}}$ and $\kappa^{\mathbf{F}}$ are provided in Appendix B.5.

It should be noted that Propositions 6 and 7 generalize the previous results on the effects of information sharing in supply chains (see Propositions 4 and 5 in Ha et al. (2011)) considering the impact of full information sharing on the platform itself and decomposing the overall effect into direct and side effects. Using these results, we can now characterize the equilibrium information sharing strategies for competing supply chains. Specifically, each supply chain i's contract choice is equivalent to manufacturer i selecting from the action space $\mathbf{Y}_i \in \{\mathbf{P},\mathbf{F}\}$, according to the decision rule shown in Proposition 7(c). Thus, the two manufacturers' choices of information sharing strategies can be viewed as a Nash game with simultaneous moves from their respective action spaces $\mathbf{Y}_i \times \mathbf{Y}_j \in \{\mathbf{P},\mathbf{F}\} \times \{\mathbf{P},\mathbf{F}\}$. It is straightforward to verify that $\kappa^{\mathbf{P}} < \kappa^{\mathbf{F}}$. By defining the terms $\zeta^{\mathbf{FF}} := \frac{4(6-\gamma+k)^2}{(4(k+6)-\gamma^2)^2}, \zeta^{\mathbf{FP}} := \frac{2}{(\gamma+4)^2} + \frac{2(6-\gamma+k)^2}{(4(k+6)-\gamma^2)^2}$, and $\zeta^{\mathbf{PP}} := \frac{4}{(\gamma+4)^2}$, we can summarize the platform's equilibrium information sharing strategies as follows.

Proposition 8. *For competing supply chains, we have the following:*

(a) The equilibrium information sharing choices are as follows: (i) if $k \geq \kappa^{\mathbf{F}}$, then $(\mathbf{F},\mathbf{F})$ is the unique equilibrium strategy; (ii) if $\kappa^{\mathbf{P}} \leq k \leq \kappa^{\mathbf{F}}$, then $(\mathbf{P},\mathbf{F})$ and $(\mathbf{F},\mathbf{P})$ are two possible equilibria strategies; (iii) if $k < \kappa^{\mathbf{P}}$, then $(\mathbf{P},\mathbf{P})$ is the unique equilibrium strategy.

(b) With possible side payments, the platform's gross payoff is given by

$$\frac{4\pi^2}{(\gamma+k+6)^2} + ((\alpha+(2s-r)\ell)^2 v_1 + \ell^2 v_2)\zeta, \tag{14}$$

where the parameter ζ is defined as follows: if $k > \kappa^{\mathbf{F}}$, then $\zeta = \zeta^{\mathbf{FF}}$; if $\kappa^{\mathbf{P}} \leq k \leq \kappa^{\mathbf{F}}$, then $\zeta = \zeta^{\mathbf{FP}}$; otherwise, $\zeta = \zeta^{\mathbf{PP}}$.

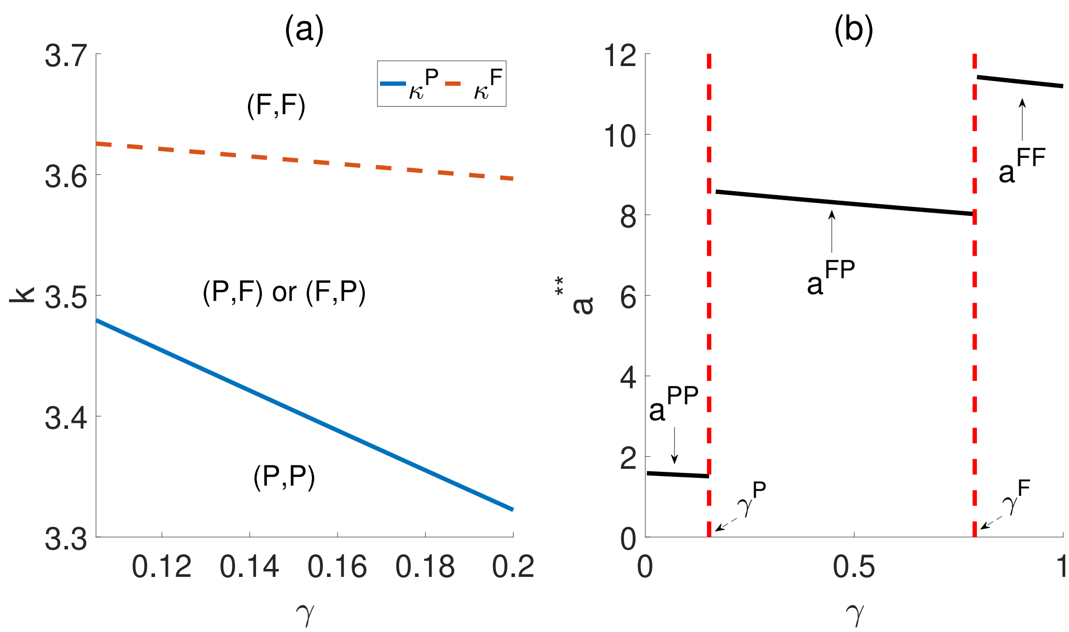
(c) The thresholds $(\kappa^{\mathbf{P}}, \kappa^{\mathbf{F}})$ given in part (a) are both decreasing as the competition intensity γ increases, and their difference, $\kappa^{\mathbf{F}} - \kappa^{\mathbf{P}}$, increases as γ increases.

Part (a) of Proposition 8 characterizes the conditions for equilibrium information sharing strategies to competing supply chains, in terms of the parameter k of production diseconomy and two thresholds $\{\kappa^{\mathbf{P}}, \kappa^{\mathbf{F}}\}$ (which further depend on γ); see Figure 2(a). First, if k is sufficiently large such that $k > \kappa^{\mathbf{F}}$, the manufacturer in each supply chain is incentivized to induce full information sharing, regardless of the rival supply chain's information arrangement. Consequently, the platform implements a complete symmetric information sharing strategy for competing supply chains, i.e., $(\mathbf{F},\mathbf{F})$ is the unique equilibrium. Second, if k is sufficiently small such that $k < \kappa^{\mathbf{P}}$, the manufacturer in each supply chain is not incentivized to induce full information sharing, regardless of the rival supply chain's information arrangement. As a result, the platform implements a symmetric partial information sharing strategy, i.e., $(\mathbf{P},\mathbf{P})$ is the unique equilibrium. Third, if k is moderate and satisfies $\kappa^{\mathbf{P}} < k < \kappa^{\mathbf{F}}$, the manufacturer in a focal supply chain induces full information sharing only when the rival supply chain adopts partial information sharing. In this case, one supply chain adopts full information sharing while the other adopts partial information sharing, resulting in two possible equilibria: $(\mathbf{P},\mathbf{F})$ and $(\mathbf{F},\mathbf{P})$. Hence, the platform employs an asymmetric mixed information sharing strategy.

Part (b) of Proposition 8 summarizes the platform's gross payoffs under each equilibrium information sharing format. In (14), the term $\frac{4\pi^2}{(\gamma+k+6)^2}$ represents the value derived from public prior information, while the term $((\alpha+(2s-r)\ell)^2 v_1 + \ell^2 v_2)\zeta$ represents the value of the platform's private information about spot freight rates. Additionally, the constant $\tilde{v}$, which represents the marginal value of the platform's information sharing, varies as the equilibrium information sharing format changes. It is straightforward to verify that ζ decreases as the equilibrium information sharing format transitions from symmetric full information sharing to symmetric partial information sharing.

Part (c) of Proposition 8 also reveals the impact of supply chain competition on the equilibrium information sharing formats; see Figure 2(a). As the competition intensity γ increases, symmetric partial information sharing becomes less likely to be chosen (since $\kappa^{\mathbf{P}}$ decreases with increasing γ), while symmetric full information sharing becomes more likely (since $\kappa^{\mathbf{F}}$ also decreases with increasing γ). In addition, asymmetric mixed information sharing is more likely to be adopted as well since the difference $\kappa^{\mathbf{F}} - \kappa^{\mathbf{P}}$ is increasing in γ.

Figure 2 The platform's information sharing for competing supply chains. Figure (a) depicts the boundary conditions for equilibrium information sharing strategies in the parameter space (γ, k). Figure (b) visualizes the comparative statics of the platform's optimal prediction accuracy a^{**} for different values of γ and fixed k, where $\gamma^{\mathbf{P}}$ and $\gamma^{\mathbf{F}}$ are unique solutions for the equations $\kappa^{\mathbf{P}}(\gamma) = k$ and $\kappa^{\mathbf{F}}(\gamma) = k$



Based on the above results, we are now ready to examine the platform's problem of maximizing its net payoff, which is the platform's equilibrium gross payoff minus the information cost, by optimizing the accuracy a of its private information. Specifically, the platform solves the following problem:

$$\max_{a \geq 4} \left\{ \frac{4\pi^2}{(\gamma + k + 6)^2} + ((\alpha + (2s - r)\ell)^2 v_1(a) + \ell^2 v_2(a))\zeta - w\,a \right\},$$

Let a^{**} denote the platform's optimal accuracy decision in competing supply chains. Recall from Proposition 8 that the parameter ζ varies as the platform's equilibrium information sharing formats change. To ensure that the optimal accuracy decision a^{**} is positive, we make the following assumption:

$$w \leq \zeta^{\mathbf{PP}} (\alpha + (2s - r)\ell)^2 \eta^2.$$

For all the equilibrium information sharing formats, we define the following solution: $a^{\mathbf{FF}} := \arg\max_{a\in\mathbb{R}_+}\{((\alpha + (2s - r)\ell)^2 v_1(a) + \ell^2 v_2(a))\zeta^{\mathbf{FF}} - w\,a\}$, $a^{\mathbf{FP}} := \arg\max_{a\in\mathbb{R}_+}\{((\alpha + (2s - r)\ell)^2 v_1(a) + \ell^2 v_2(a))\zeta^{\mathbf{FP}} - w\,a\}$ and $a^{\mathbf{PP}} := \arg\max_{a\in\mathbb{R}_+}\{((\alpha + (2s - r)\ell)^2 v_1(a) + \ell^2 v_2(a))\zeta^{\mathbf{PP}} - w\,a\}$.

PROPOSITION 9. *For competing supply chains,*

(a) The platform's optimal prediction accuracy a^{**} has a piecewise form as follows:

$$a^{**} = \begin{cases} a^{\mathbf{FF}}, & \text{if } k > \kappa^{\mathbf{F}}, \\ a^{\mathbf{FP}}, & \text{if } \kappa^{\mathbf{P}} \le k \le \kappa^{\mathbf{F}}, \\ a^{\mathbf{PP}}, & \text{if } k < \kappa^{\mathbf{P}}, \end{cases}$$

where $a^{\mathbf{FF}} \ge a^{\mathbf{FP}} \ge a^{\mathbf{PP}}$.

(b) $a^{\mathbf{FF}}$, $a^{\mathbf{FP}}$ and $a^{\mathbf{PP}}$ all increase as the sensitivity coefficient ℓ of freight rejection increases.

(c) $a^{\mathbf{FF}}$, $a^{\mathbf{FP}}$ and $a^{\mathbf{PP}}$ all decrease as the coefficient γ of competition intensity increases.

Proof. See Appendix B.7. □

From Proposition 9 we find that in competing supply chains, the platform's optimal prediction accuracy has a piecewise form that depends on the coefficient k of production diseconomy. Specifically, a^{**} is composed of the three terms $a^{\mathbf{FF}}$, $a^{\mathbf{FP}}$ and $a^{\mathbf{PP}}$, which represent the optimal prediction accuracy under symmetric full information sharing, asymmetric mixed information sharing, and symmetric partial information sharing, respectively.

Furthermore, since $\zeta^{\mathbf{PP}} \le \zeta^{\mathbf{FP}} \le \zeta^{\mathbf{FF}}$, we also obtain the inequality $a^{\mathbf{PP}} \le a^{\mathbf{FP}} \le a^{\mathbf{FF}}$, indicating that the platform would improve the accuracy of its private information as the information sharing format transitions from symmetric full information sharing to symmetric partial information sharing. Additionally, Proposition 9(b) shows that the terms $a^{\mathbf{FF}}$, $a^{\mathbf{FP}}$, and $a^{\mathbf{PP}}$ are increasing with respect to the sensitivity coefficient ℓ of freight rejection, which is consistent with the previous finding in Proposition 4.

Proposition 9(c) reveals the impact of supply chain competition on the platform's optimal prediction accuracy decision. As the coefficient γ of competition intensity increases, the marginal values $\zeta^{\mathbf{FF}}$, $\zeta^{\mathbf{FP}}$, and $\zeta^{\mathbf{PP}}$ associated with the platform's information sharing strategies decrease, compelling the platform to reduce prediction accuracy under every equilibrium information sharing format (i.e., $a^{\mathbf{FF}}$, $a^{\mathbf{FP}}$, and $a^{\mathbf{PP}}$ all decrease as γ increases). Interestingly, the monotonic behavior of $a^{\mathbf{FF}}$, $a^{\mathbf{FP}}$, and $a^{\mathbf{PP}}$ with respect to γ does not necessarily imply that the platform's optimal prediction accuracy decision a^{**} is decreasing in γ. In particular, as illustrated by Figure 2(b), although the platform's prediction accuracy decision is decreasing in γ under every equilibrium format, there are jumps in prediction accuracy when the platform switches between equilibrium information sharing formats. For example, a^{**} jumps from $a^{\mathbf{FP}}$ to $a^{\mathbf{FF}}$ as the platform switches from an asymmetric mixed information sharing to a symmetric full information sharing.

In prior studies on information sharing (e.g., Ha et al. (2011, 2017) and Liu et al. (2021)), the prediction accuracy is assumed to be exogenous. Proposition 9 complements these studies by endogenizing the prediction accuracy as the platform's decision and revealing the interesting role of supply chain competition in shaping the platform's prediction accuracy. Intuitively, one might expect the platform to increase prediction accuracy as competition intensifies because the signal becomes more attractive to supply chains that want to gain a competitive advantage. As shown by Proposition 9, this expectation is partially correct because as the competition increases, the platform experiences sudden stepwise improvements in its prediction accuracy as it switches equilibrium information sharing formats. However, under every equilibrium information sharing format, the platform's optimal prediction accuracy decreases as the competition intensity increases. This result highlights the need for a digital freight brokerage platform to be cautious in strategically investing in prediction accuracy for different degrees of supply chain competition.

6. Concluding Remarks

Motivated by real-world supply chain logistics practices, this paper examined how digital freight platforms share their information on spot freight rates with companies in supply chains to improve their operations in anticipation of freight rejection. We characterized the equilibrium information sharing strategy (either partial or full information sharing) by a digital freight platform for a single supply chain consisting of a retailer and a manufacturer, and explored the platform's optimal prediction accuracy under the equilibrium strategy.

We then extended our analysis by considering information sharing of a digit freight platform to competing supply chains. We identified three information sharing formats: (a) symmetric full information sharing, (b) asymmetric mixed information sharing, and (c) symmetric partial information sharing. As the upstream production diseconomy increases, the platform gradually shifts from symmetric partial information sharing to symmetric full information sharing. Moreover, the impact of increasing the sensitivity coefficient of freight rejection on the platform's optimal prediction accuracy continues to hold in the case of supply chain competition.

This research provides several insights for digital freight platforms looking to implement an information sharing program to supply chains. First, our results indicate that the core of a platform's information sharing program lies in its prediction accuracy, suggesting that a platform should invest more in improving prediction accuracy as the probability of freight rejection increases. Second, the platform should be aware of the impact of supply chain competition on its investment in prediction accuracy. Unlike prior findings in the literature (e.g., Ha et al. (2011), Huang et al. (2018), Ha et al.

(2022), Shi et al. (2021)), we show that a significant increase in competition intensity can lead to sudden stepwise improvements in prediction accuracy as the platform switches between equilibrium information sharing formats. However, a slight increase in competition intensity may discourage the platform from improving its prediction accuracy under every equilibrium information sharing format. Third, this work provides insights into the ongoing debates on freight rejection (Scott et al. 2017, Acocella 2022) by demonstrating that information sharing by digital freight platforms can serve as an effective solution for managing freight rejection. However, supply chain practitioners should be careful with mixed use of platforms' information sharing and other existing solution (e.g., flexible freight contract) because of the negative spillover effect of platforms' information sharing.

This paper can be extended in several ways. First, motivated by the practice of the online freight platform mentioned in the introduction—specifically, that most of the platform's clients are downstream retailers in supply chains—we assume that the platform directly shares information with retailers under partial information sharing. Considering that a platform's clients can also be upstream manufacturers in practice, it would be interesting to extend our model by analyzing partial information sharing exclusively with upstream manufacturers. Second, the main findings of this paper suggest that the double marginalization effect in a supply chain subject to freight rejection can be affected by the probability of freight rejection. A potential future research direction would be to conduct an empirical study to examine the impact of freight rejection probability on double marginalization within supply chains.

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E-companion

The E-companion is organized as follows. All the proofs of the results for the single supply chain model are shown in Appendix A. The proofs of the results for the competing supply chain model are shown in Appendix B. Finally, an extension of the single supply chain model is studied in Appendix C.

Appendix A: Single Supply Chain

A.1. Proof of Lemma 1

We derive every player's equilibrium decision in the baseline setting as follows. First, the retailer maximizes the expected profit, $\mathbb{E}\left[(u-q-w-r_e)q\right]=q(c-q-\rho(\alpha+s\ell)-w+\pi)$, with the order quantity: $\tilde{q}(w,\rho)=\frac{1}{2}\left(-\alpha\rho+c-\rho s\ell-w+\pi\right)$. Then, the manufacturer maximizes the expected profit, $\tilde{q}(w,\rho)(w-c)-\frac{k}{2}\tilde{q}(w,\rho)^2$, with the wholesale price: $\tilde{w}(q)=c+\frac{(k+2)(\pi-\rho(\alpha+s\ell))}{k+4}$. Meanwhile, the platform maximizes the expected profit, $\mathbb{E}\left[\rho\,\tilde{q}(w,\rho)\delta(S)|\Psi\right]$, with the brokerage fee: $\rho(w)=\frac{c-w+\pi}{2\alpha+2s\ell}$. By jointly considering the manufacturer's and platform's best responses, we obtain:

$$w^{\mathbf{N}}=c+\frac{\pi(k+2)}{k+6},\rho^{\mathbf{N}}=\frac{2\pi}{(k+6)(\alpha+s\ell)}$$

By substituting $w^{\mathbf{N}}$ and $\rho^{\mathbf{N}}$ into $\tilde{q}(\cdot)$, we further have the supply chain's equilibrium retail quantity:

$$q^{\mathbf{N}}=\frac{\pi}{k+6}.$$

Furthermore, based on the equilibrium decisions, we further obtain every player's ex-ante payoffs shown in (5). $\square$

A.2. Proof of Proposition 1

We first prove the result in the case of partial information sharing. First, the retailer maximizes the expected profit conditioned on Ψ, $\mathbb{E}\left[(u-q-w-r_f(S))\,q|\Psi\right]=q\left(c-\alpha(\mathbb{E}\left[\epsilon|\Psi\right]+\rho)+\ell(\mathbb{E}\left[\epsilon|\Psi\right]r-\mathbb{E}\left[\epsilon|\Psi\right](\rho+2s)-\mathbb{E}\left[\epsilon^2|\Psi\right]+\eta-\rho s)-q-w+\pi\right)$, with the following order quantity:

$$\breve{q}(w,\rho,\Psi)=\frac{1}{2}(c-\alpha(\mathbb{E}\left[\epsilon|\Psi\right]+\rho)+\ell(\mathbb{E}\left[\epsilon|\Psi\right]r-\mathbb{E}\left[\epsilon|\Psi\right](\rho+2s)-\mathbb{E}\left[\epsilon^2|\Psi\right]+\eta-\rho s)-w+\pi). \tag{15}$$

Given the conjecture w on the wholesale price, the platform maximizes the expected profit conditioned on Ψ, $\mathbb{E}\left[\rho\,\delta(S)\,\breve{q}(\cdot)|\Psi\right]$, with the wholesale price:

$$\breve{\rho}(w,\Psi)=\frac{c-\alpha\mathbb{E}\left[\epsilon|\Psi\right]+\ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s)-\mathbb{E}\left[\epsilon^2|\Psi\right]+\eta)-w+\pi}{2(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))}.$$

Meanwhile, given the conjecture ρ on the brokerage fee (which is actually a function of Ψ), the manufacturer maximizes the expected profit based solely on prior information $\mathbb{E}\left[\breve{q}(\cdot)(w-c)-\frac{k}{2}\breve{q}(\cdot)^2\right]$, with the following wholesale price:

$$\breve{w}(\rho(\Psi))=c+\frac{(k+2)(-\mathbb{E}\left[\rho(\Psi)(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))\right]+\pi(k+2)}{k+4}. \tag{16}$$

By observing the two players' best responses (15) and (16), we find that the following equilibrium decisions,

$$w^{\mathbf{P}}=c+\frac{\pi(k+2)}{k+6},\rho^{\mathbf{P}}=\frac{(k+6)(\ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s)-\mathbb{E}\left[\epsilon^2|\Psi\right]+\eta)-\alpha\mathbb{E}\left[\epsilon|\Psi\right])+4\pi}{2(k+6)(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))}, \tag{17}$$

which simultaneously fulfill these two response functions. Moreover, using the technique (Claim 1) in Ha et al. (2011), we can prove the uniqueness of $(w^{\mathbf{P}}, \rho^{\mathbf{P}})$. By substituting $(w^{\mathbf{P}}, \rho^{\mathbf{P}})$ into $\breve{q}(\cdot)$, we obtain the supply chain's equilibrium retail quantity in the case of partial information sharing as follows:

$$q^{\mathbf{P}} = q^{\mathbf{N}} + \frac{1}{4}(\ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s) - \mathbb{E}\left[\epsilon^2|\Psi\right] + \eta) - \alpha\mathbb{E}\left[\epsilon|\Psi\right]).$$

Moreover, we also obtain all the players' payoffs as follows:

$$\begin{aligned}
\Pi_R^{\mathbf{P}} &= \Pi_R^{\mathbf{N}} + \frac{v_1(\alpha - r\ell + 2s\ell)^2 + v_2\ell^2}{16}, \\
\Pi_M^{\mathbf{P}} &= \Pi_M^{\mathbf{N}} - \frac{kv_1(\alpha - r\ell + 2s\ell)^2 + kv_2\ell^2}{32}, \\
\Pi_P^{\mathbf{P}} &= \Pi_P^{\mathbf{N}} + \frac{v_1(\alpha - r\ell + 2s\ell)^2 + v_2\ell^2}{8}
\end{aligned}$$

Next, we consider the case of full information sharing, in which the retailer's optimal order quantity and the platform's optimal brokerage fee still follow $\breve{q}(\cdot)$ and $\breve{\rho}(\cdot)$, respectively. Then, the manufacturer maximizes the expected profit conditioned on Ψ, $\mathbb{E}\left[\breve{q}(\cdot)(w-c) - \frac{k}{2}\breve{q}(\cdot)^2|\Psi\right]$, with the following wholesale price:

$$\breve{w}'(\rho) = \frac{2(-\alpha\mathbb{E}\left[\epsilon|\Psi\right] + \ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s) - \mathbb{E}\left[\epsilon^2|\Psi\right] + \eta) + \pi)}{(k+6)(\alpha + \ell(\mathbb{E}\left[\epsilon|\Psi\right] + s))}. \tag{18}$$

By jointly considering the response functions (15) and (18), we obtain the equilibrium wholesale price and brokerage fee in the case of full information sharing:

$$w^{\mathbf{F}} = c + \frac{(k+2)(\pi - \alpha\mathbb{E}\left[\epsilon|\Psi\right] + \ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s) - \mathbb{E}\left[\epsilon^2|\Psi\right] + \eta))}{k+6}, \rho^{\mathbf{F}} = \frac{2(\pi - \alpha\mathbb{E}\left[\epsilon|\Psi\right] + \ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s) - \mathbb{E}\left[\epsilon^2|\Psi\right] + \eta))}{(k+6)(\alpha + \ell(\mathbb{E}\left[\epsilon|\Psi\right] + s))}.$$

By substituting $(w^{\mathbf{F}}, \rho^{\mathbf{F}})$ into $\breve{q}(\cdot)$, we have the supply chain's equilibrium retail quantity:

$$q^{\mathbf{F}} = q^{\mathbf{N}} + \frac{\ell(-(2s-r)\mathbb{E}\left[\epsilon|\Psi\right] - \mathbb{E}\left[\epsilon^2|\Psi\right] + \eta) - \alpha\mathbb{E}\left[\epsilon|\Psi\right]}{k+6}.$$

Moreover, all the players' payoffs as follows:

$$\begin{aligned}
\Pi_R^{\mathbf{F}} &= \Pi_R^{\mathbf{N}} + \frac{v_1(\alpha - r\ell + 2s\ell)^2 + v_2\ell^2}{(k+6)^2}, \\
\Pi_M^{\mathbf{F}} &= \Pi_M^{\mathbf{N}} + \frac{(k+4)\left(v_1(\alpha - r\ell + 2s\ell)^2 + v_2\ell^2\right)}{2(k+6)^2}, \\
\Pi_P^{\mathbf{F}} &= \Pi_P^{\mathbf{N}} + \frac{2\left(v_1(\alpha - r\ell + 2s\ell)^2 + v_2\ell^2\right)}{(k+6)^2},
\end{aligned}$$

which completes the proof. □

A.3. Proof of Proposition 2

Based on Proposition 1, we have:

$$\begin{aligned}
&\Pi_R^{\mathbf{P}} - \Pi_R^{\mathbf{N}} > 0, \Pi_M^{\mathbf{P}} - \Pi_M^{\mathbf{N}} < 0, \quad \Pi_P^{\mathbf{P}} - \Pi_P^{\mathbf{N}} > 0 \\
&\Pi_R^{\mathbf{F}} - \Pi_R^{\mathbf{N}} > 0, \Pi_M^{\mathbf{F}} - \Pi_M^{\mathbf{N}} > 0, \quad \Pi_P^{\mathbf{F}} - \Pi_P^{\mathbf{N}} > 0.
\end{aligned} \tag{19}$$

Moreover, we also have:

$$\Pi_R^{\mathbf{F}} - \Pi_R^{\mathbf{P}} < 0, \Pi_P^{\mathbf{F}} - \Pi_P^{\mathbf{P}} < 0, \Pi_M^{\mathbf{F}} - \Pi_M^{\mathbf{P}} > 0, \tag{20}$$

which completes the proof. □

A.4. Proof of Proposition 3

From Proposition 1, we know that the manufacturer's net value of full information sharing, under the side payments to the retailer and the platform, is expressed by:

$$\Pi_M^{\mathbf{F}} - \Pi_M^{\mathbf{P}} + (\Pi_R^{\mathbf{F}} - \Pi_R^{\mathbf{P}}) + (\Pi_P^{\mathbf{F}} - \Pi_P^{\mathbf{P}}) = \frac{(k+2)(k^2+4k-28)\left(v_1(\alpha - r\ell + 2s\ell)^2 + v_2\ell^2\right)}{32(k+6)^2}, \tag{21}$$

which is positive only when $k > 2(2\sqrt{2}-1)$.

Furthermore, the platform's gross payoff with possible side payment is equivalent to $\Pi_P^{\mathbf{P}} = \frac{2\pi^2}{(k+6)^2} + \frac{1}{8}\left(v_1(\alpha - r\ell + 2s\ell)^2 + v_2\ell^2\right)$. □

Appendix B: Competing Supply Chains

B.1. Proof of Proposition 5

We first consider a focal supply chain i's best response function based on retailer i's and manufacturer i's common conjecture q_j about rival supply chain j's retail quantity. Specifically, in the case of no information sharing, the retailer i maximizes the expected profit, $\mathbb{E}\left[q_i\left(-q_i - \gamma q_j - r + u - w\right)\right]$, with the order quantity:

$$q_i^{\mathbf{N}}(w_i, \rho_i, q_j) = \frac{1}{2}\left(c - \gamma\mathbb{E}\left[q_j\right] - \rho_i(\alpha + s\ell) - w + \pi\right).$$

Given the conjecture about the wholesale price w_i, the platform maximizes its expected profit, $\mathbb{E}\left[\rho_i\,\delta(S)\,q_i^{\mathbf{N}}(w_i, \rho_i, q_j)|\Psi\right]$, with the following brokerage fee:

$$\rho_i^*(w_i, q_j) = \frac{c - \gamma\mathbb{E}\left[q_j\right] - w_i + \pi}{2(\alpha + s\ell)}.$$

Meanwhile, given the conjecture about the brokerage fee ρ_i, the manufacturer i maximizes his expected profit, $\mathbb{E}\left[(w_i - c)q_i^{\mathbf{N}}(w_i, \rho_i, q_j) - \frac{k}{2}q_i^{\mathbf{N}}(w_i, \rho_i, q_j)^2\right]$, with the wholesale price:

$$w_i^*(\rho_i, q_j) = \frac{c(k+4) - \gamma(k+2)\mathbb{E}\left[q_j\right] + (k+2)(\pi - \rho(\alpha + s\ell))}{k+4}.$$

By jointly consider the response functions $\rho_i^*(w_i, q_j)$ and $w_i^*(\rho_i, q_j)$, we obtain the equilibrium wholesale price and brokerage fee, denoted by $w_i^{\mathbf{N}}$ and $\rho_i^{\mathbf{N}}$, in the case of no information sharing as follows:

$$w_i^{\mathbf{N}} = \frac{c(k+6) - \gamma(k+2)\mathbb{E}\left[q_j\right] + \pi(k+2)}{k+6}, \rho_i^{\mathbf{N}} = \frac{2\left(\pi - \gamma\mathbb{E}\left[q_j\right]\right)}{(k+6)(\alpha + s\ell)}.$$

By substituting $w_i^{\mathbf{N}}$ and $\rho_i^{\mathbf{N}}$ into $q^{\mathbf{N}}(\cdot)$, we obtain supply chain i's best response function in the case of no information sharing as follows:

$$\hat{q}_i^{\mathbf{N}}(q_j) = \frac{\pi - \gamma\mathbb{E}\left[q_j\right]}{k+6}. \tag{22}$$

Apparently, the above analysis of supply chain i's best response function is the same as that of single supply chain's equilibrium retail quantity shown in previous section.

Similarly, it can be shown that supply chain i's equilibrium wholesale price and brokerage fee, denoted by $w_i^{\mathbf{P}}$ and $\rho_i^{\mathbf{P}}$, in the case of partial information sharing as follows:

$$w_i^{\mathbf{P}} = \frac{c(k+6) - \gamma(k+2)\mathbb{E}\left[q_j\right] + \pi(k+2)}{k+6},$$
$$\rho_i^{\mathbf{P}} = \frac{-\gamma(k+6)\mathbb{E}\left[q_j|\Psi\right] + (k+6)(\ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s) - \mathbb{E}\left[\epsilon^2|\Psi\right] + \eta) - \alpha\mathbb{E}\left[\epsilon|\Psi\right]) + \gamma(k+2)\mathbb{E}\left[q_j\right] + 4\pi}{2(k+6)(\alpha + \ell(\mathbb{E}\left[\epsilon|\Psi\right] + s))}.$$

While, the supply chain i's best response function in the case of partial information sharing is as follows:

$$\hat{q}_i^{\mathbf{P}}(q_j) = \frac{-\gamma(k+6)\mathbb{E}[q_j|\Psi] + (k+6)(\ell(\mathbb{E}[\epsilon|\Psi](r-2s) - \mathbb{E}[\epsilon^2|\Psi] + \eta) - \alpha\mathbb{E}[\epsilon|\Psi]) + \gamma(k+2)\mathbb{E}[q_j] + 4\pi}{4(k+6)}. \quad (23)$$

Furthermore, supply chain i's equilibrium wholesale price and brokerage fee, denoted by $w_i^{\mathbf{F}}$ and $\rho_i^{\mathbf{F}}$, in the case of full information sharing as follows:

$$w_i^{\mathbf{F}} = \frac{c(k+6) - \gamma(k+2)\mathbb{E}[q_j|\Psi] + (k+2)(-\alpha\mathbb{E}[\epsilon|\Psi] + \ell(\mathbb{E}[\epsilon|\Psi](r-2s) - \mathbb{E}[\epsilon^2|\Psi] + \eta) + \pi)}{k+6},$$
$$\rho_i^{\mathbf{F}} = \frac{2(-\alpha\mathbb{E}[\epsilon|\Psi] - \gamma\mathbb{E}[q_j|\Psi] + \ell(\mathbb{E}[\epsilon|\Psi](r-2s) - \mathbb{E}[\epsilon^2|\Psi] + \eta) + \pi)}{(k+6)(\alpha + \ell(\mathbb{E}[\epsilon|\Psi] + s))}.$$

While, the supply chain i's best response function in the case of full information sharing is as follows:

$$\hat{q}_i^{\mathbf{F}}(q_j) = \frac{-\alpha\mathbb{E}[\epsilon|\Psi] - \gamma\mathbb{E}[q_j|\Psi] + \ell(\mathbb{E}[\epsilon|\Psi](r-2s) - \mathbb{E}[\epsilon^2|\Psi] + \eta) + \pi}{k+6}. \quad (24)$$

Using (22)$\sim$(24), we reverse the roles of i and j and obtain the response functions (retail quantity) of rival supply chain $q_j^{\mathbf{Y}_j}(q_i)$, for $\mathbf{Y}_j \in \{\mathbf{N}, \mathbf{P}, \mathbf{F}\}$, by assuming the conjecture q_i about focal supply chain i's retail quantity.

Next, based on competing supply chains' response functions $q_i^{\mathbf{Y}_i}(q_j)$ and $q_j^{\mathbf{Y}_j}(q_i)$, we can obtain the BNE retail quantities. For example, when the platform does not share any information with either of the two supply chains (i.e., $\mathbf{Y}_i = \mathbf{Y}_j = \mathbf{N}$), it is easy to verify that the pair of retail quantities, $q_i^{\mathbf{NN}} = \frac{\pi}{\gamma+k+6}, q_j^{\mathbf{NN}} = \frac{\pi}{\gamma+k+6}$, satisfies the best response functions. Moreover, using Claim 1 in Ha et al. (2011), we can show the uniqueness of $\{q_i^{\mathbf{NN}}, q_j^{\mathbf{NN}}\}$. The BNE retail quantities for the information arrangements can be proved similarly. $\square$

B.2. Retailer i's payoff $\Pi_{R_i}^{\mathbf{Y}_i}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i})$, manufacturer i's payoff $\Pi_{M_i}^{\mathbf{Y}_i}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i})$, and the platform's payoff $\Pi_{P_i}^{\mathbf{Y}_i}(\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i})$ of serving retailer i, depending on rival supply chain j's competitive response $\phi_j^{\mathbf{Y}_j,\mathbf{Y}_i}$

Given $\phi_j = (\phi_{j_0}, \phi_{j_1}, \phi_{j_2})$, we define the following functions: $\bar{\Pi}_R(\phi_j) := \frac{(\frac{\pi(k+6)}{\gamma+k+6} - \gamma\eta(\phi_{j_0}+\phi_{j_2}))^2}{(k+6)^2}$, $\bar{\Pi}_M(\phi_j) := \frac{(k+4)(\frac{\pi(k+6)}{\gamma+k+6} - \gamma\eta(\phi_{j_0}+\phi_{j_2}))^2}{2(k+6)^2}$, $\bar{\Pi}_{P_i}(\phi_j) := \frac{2(\frac{\pi(k+6)}{\gamma+k+6} - \gamma\eta(\phi_{j_0}+\phi_{j_2}))^2}{(k+6)^2}$, and $\Delta(\phi_j) := (\alpha + \phi_{j_1}\gamma + (2s-r)\ell)^2 v_1 + (\gamma\phi_{j_2} + \ell)^2 v_2$. Then, retailer i's payoff, manufacturer i's payoff, and the platform's payoff of serving retailer i, are respectively expressed as follows:

(a) In the case of no information sharing (i.e., $\mathbf{Y}_i = \mathbf{N}$),

$$\Pi_{R_i}^{\mathbf{N}}(\phi_j^{\mathbf{Y}_j,\mathbf{N}}) = \bar{\Pi}_R(\phi_j^{\mathbf{Y}_j,\mathbf{N}}), \Pi_{M_i}^{\mathbf{N}}(\phi_j^{\mathbf{Y}_j,\mathbf{N}}) = \bar{\Pi}_M(\phi_j^{\mathbf{Y}_j,\mathbf{N}}), \Pi_{P_i}^{\mathbf{N}}(\phi_j^{\mathbf{Y}_j,\mathbf{N}}) = \bar{\Pi}_P(\phi_j^{\mathbf{Y}_j,\mathbf{N}}). \quad (25)$$

(b) In the case of partial information sharing (i.e., $\mathbf{Y}_i = \mathbf{P}$),

$$\Pi_{R_i}^{\mathbf{Y}_i}(\phi_j^{\mathbf{Y}_j,\mathbf{P}}) = \bar{\Pi}_R(\phi_j^{\mathbf{Y}_j,\mathbf{P}}) + \frac{\Delta(\phi_j^{\mathbf{Y}_j,\mathbf{P}})}{16}, \Pi_{M_i}^{\mathbf{P}}(\phi_j^{\mathbf{Y}_j,\mathbf{P}}) = \bar{\Pi}_M(\phi_j^{\mathbf{Y}_j,\mathbf{P}}) - k\frac{\Delta(\phi_j^{\mathbf{Y}_j,\mathbf{P}})}{32}, \Pi_{P_i}^{\mathbf{P}}(\phi_j^{\mathbf{Y}_j,\mathbf{P}}) = \bar{\Pi}_P(\phi_j^{\mathbf{Y}_j,\mathbf{P}}) + \frac{\Delta(\phi_j^{\mathbf{Y}_j,\mathbf{P}})}{8}. \quad (26)$$

(c) In the case of full informatin sharing (i.e., $\mathbf{Y}_i = \mathbf{F}$),

$$\Pi_{R_i}^{\mathbf{F}}(\phi_j^{\mathbf{Y}_j,\mathbf{F}}) = \bar{\Pi}_R(\phi_j^{\mathbf{Y}_j,\mathbf{F}}) + \frac{\Delta(\phi_j^{\mathbf{Y}_j,\mathbf{F}})}{(k+6)^2}, \Pi_{M_i}^{\mathbf{F}}(\phi_j^{\mathbf{Y}_j,\mathbf{F}}) = \bar{\Pi}_M(\phi_j^{\mathbf{Y}_j,\mathbf{F}}) + \frac{\Delta(\phi_j^{\mathbf{Y}_j,\mathbf{F}})}{2(k+6)^2}, \Pi_{P_i}^{\mathbf{F}}(\phi_j^{\mathbf{Y}_j,\mathbf{F}}) = \bar{\Pi}_P(\phi_j^{\mathbf{Y}_j,\mathbf{F}}) + \frac{\Delta(\phi_j^{\mathbf{Y}_j,\mathbf{F}})}{(k+6)^2}. \quad (27)$$

B.3. Proof of Proposition 4

In this proof, we define $A = a\eta + 1$ and use A as the decision variable, rather than a. As a result, the platform's problem becomes

$$\max_{A\geq 1}\{G(A)\} = \max_{A\geq 1}\left\{\frac{2\pi(\ell)^2}{(k+6)^2} + \frac{(A-1)\eta\,(A(\alpha - r\ell + 2s\ell)^2 + 2(A-1)\eta\ell^2)}{8A^2} - \frac{w - Aw}{\eta}\right\},$$

where $\pi(\ell) := -c + r(\alpha + s\ell - 1) - s(\alpha + s\ell) + u - \eta\ell\}$ is decreasing in ℓ.

By applying the FOC, we consider the first-order derivative of the platform's objective function $G(A)$ as follows:

$$\frac{dG(A)}{dA} = \frac{\eta\,(A(\alpha - r\ell + 2s\ell)^2 + 4(A-1)\eta\ell^2)}{8A^3} - \frac{w}{\eta},$$

which is a function that cross the zero line single time, from positive to negative, when $\frac{dG(A)}{dA}|_{A=1} > 0$. In particular, $\frac{dG(A)}{dA}|_{A=1} > 0$ is equivalent to $w < \frac{1}{8}\eta^2(\alpha - r\ell + 2s\ell)^2$. This result proves the quasiconcavity of the $G(A)$, such that the optimal solution $A^* = \arg\max_{A\geq 1}\{G(A)\}$ is unique, i.e., $a^* = \frac{A^*-1}{\eta}$ is unique.

Next, we consider the cross derivative of the objective function:

$$\frac{\partial^2 G}{\partial A \partial \ell} = \frac{\eta(A(2s-r)(\alpha - r\ell + 2s\ell) + 4(A-1)\eta\ell)}{4A^3} \geq 0,$$

which means that the objective function $G(\cdot)$ is supermodular in (A, ℓ). As such, the optimal solution $A^*(\ell)$ is increasing in ℓ, which implies that $a^*(\ell) = \frac{A^*(\ell)-1}{\eta}$ is also increasing.

Finally, we prove the convexity of the optimal value $G(A^*)$. Note that the term $\frac{2\pi(\ell)^2}{(k+6)^2}$ is convex in ℓ. It suffices to show that the function $\bar{G}(A^*) = \frac{(A^*-1)\eta\left(A^*(\alpha - r\ell + 2s\ell)^2 + 2(A^*-1)\eta\ell^2\right)}{8(A^*)^2} - \frac{w - A^* w}{\eta}$ is also convex. We consider the second-order derivative:

$$\frac{d^2\bar{G}(A^*)}{d\ell^2} = \frac{(A^*-1)A^*\eta((2\eta(A^*-1) + A^*(r-2s)^2) + \eta(A^*(2s-r)(\alpha + (2s-r)\ell) + 4\eta\ell(A^*-1))\frac{dA^*}{d\ell}}{4(A^*)^3} \geq 0,$$

which demonstrates the convexity of $\tilde{G}(A^*)$ in ℓ. Recall that the retailer's payoff under the optimal accuracy decision is $G(A^*)/2$, which is also convex in ℓ.

When $k \leq 2\left(2\sqrt{2} - 1\right)$, partial information sharing is used in the supply chain, and the manufacturer's payoff under the optimal accuracy decision is given by:

$$\frac{\pi(\ell)^2(k+4)}{2(k+6)^2} - \frac{(A^*-1)\,\eta k\,(A^*(\alpha - r\ell + 2s\ell)^2 + 2\,(A^*-1)\,\eta\ell^2)}{32\,(A^*)^2},$$

in which the term $\frac{\pi(\ell)^2(k+4)}{2(k+6)^2}$ is decreasing in ℓ. Morever, it is easy to verify that $\frac{(A^*-1)\eta k\left(A^*(\alpha - r\ell + 2s\ell)^2 + 2(A^*-1)\eta\ell^2\right)}{32(A^*)^2}$ is increasing in ℓ given that A^* is increasing in ℓ.

When $k > \left(2\sqrt{2} - 1\right)$, full information sharing is used in the supply chain under the manufacturer's side payment. As a result, the manufacturer's net payoff, excluding the optimal accuracy decision is

$$\frac{8(k+4)\pi(l)^2 - \frac{(A^*-1)\eta(k(3k+28)+28)\left(A^*\left((\alpha - r\ell + 2s\ell)^2 + 2\eta\ell^2\right) - 2\eta\ell^2\right)}{(A^*)^2}}{16(k+6)^2},$$

which is also decreasing in ℓ. $\square$

B.4. Proof of Proposition 6

In this proof, we define $m := v_1(\alpha - r\ell + 2s\ell)^2 + v_2\ell^2 > 0$. We assess the impact of information sharing on the relevant players relative to the baseline of no information sharing as follows:

(a) When rival supply chain j's information sharing arrangement is no information sharing, the effect of partial information sharing on retailer i is given by $\Pi^{\mathbf{P}}_{R_i}(\boldsymbol{\phi}^{\mathbf{NP}}_j) - \Pi^{\mathbf{N}}_{R_i}(\boldsymbol{\phi}^{\mathbf{NN}}_j) = \frac{m}{16} > 0$ and the effect on the platform is given by $\Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{NP}}_j) + \Pi^{\mathbf{N}}_{P_j}(\boldsymbol{\phi}^{\mathbf{PN}}_i) - [\Pi^{\mathbf{N}}_{P_i}(\boldsymbol{\phi}^{\mathbf{NN}}_j) + \Pi^{\mathbf{N}}_{P_j}(\boldsymbol{\phi}^{\mathbf{NN}}_i)] = \frac{m}{8} > 0$.

Furthermore, the effect of full information sharing on retailer i and manufacturer i is given by $\Pi^{\mathbf{F}}_{R_i}(\boldsymbol{\phi}^{\mathbf{NF}}_j) - \Pi^{\mathbf{N}}_{R_i}(\boldsymbol{\phi}^{\mathbf{NN}}_j) = \frac{m}{(k+6)^2} > 0$ and $\Pi^{\mathbf{F}}_{M_i}(\boldsymbol{\phi}^{\mathbf{NF}}_j) - \Pi^{\mathbf{N}}_{M_i}(\boldsymbol{\phi}^{\mathbf{NN}}_j) = \frac{(k+4)m}{2(k+6)^2} > 0$, respectively, and the effect on the platform is given by $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{NF}}_j) + \Pi^{\mathbf{N}}_{P_j}(\boldsymbol{\phi}^{\mathbf{FN}}_i) - [\Pi^{\mathbf{N}}_{P_i}(\boldsymbol{\phi}^{\mathbf{NN}}_j) + \Pi^{\mathbf{N}}_{P_j}(\boldsymbol{\phi}^{\mathbf{NN}}_i)] = \frac{2m}{(k+6)^2} > 0$.

(b) When rival supply chain j's information sharing arrangement is partial information sharing, the effect of partial information sharing on retailer i is given by $\Pi^{\mathbf{P}}_{R_i}(\boldsymbol{\phi}^{\mathbf{PP}}_j) - \Pi^{\mathbf{N}}_{R_i}(\boldsymbol{\phi}^{\mathbf{PN}}_j) = \frac{m}{(\gamma+4)^2} > 0$ and the effect on the platform is given by $\Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{PP}}_j) + \Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{PP}}_i) - [\Pi^{\mathbf{N}}_{P_i}(\boldsymbol{\phi}^{\mathbf{PN}}_j) + \Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{NP}}_i)] = \frac{2(\gamma^4+2\gamma^3(k+2)-\gamma^2(k(k+12)+52)-8\gamma(k+2)(k+6)+16(k+6)^2)m}{(\gamma+4)^2(\gamma^2-4(k+6))^2} > 0$.

Furthermore, the effect of full information sharing on retailer i and manufacturer i is given by $\Pi^{\mathbf{F}}_{R_i}(\boldsymbol{\phi}^{\mathbf{PF}}_j) - \Pi^{\mathbf{N}}_{R_i}(\boldsymbol{\phi}^{\mathbf{PN}}_j) = \frac{(\gamma-4)^2 m}{(\gamma^2-4(k+6))^2} > 0$ and $\Pi^{\mathbf{F}}_{M_i}(\boldsymbol{\phi}^{\mathbf{PF}}_j) - \Pi^{\mathbf{N}}_{M_i}(\boldsymbol{\phi}^{\mathbf{PN}}_j) = \frac{(\gamma-4)^2(k+4)m}{2(\gamma^2-4(k+6))^2} > 0$, respectively, and the effect on the platform is given by $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{PF}}_j) + \Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{FP}}_i) - [\Pi^{\mathbf{N}}_{P_i}(\boldsymbol{\phi}^{\mathbf{PN}}_j) + \Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{NP}}_i)] = \frac{(4-\gamma)(\gamma^3+4\gamma^2-8\gamma(k+8)+64)}{8(\gamma^2-4(k+6))^2}m$, which is negative only when $k > \frac{\gamma^3+4\gamma^2-64\gamma+64}{8\gamma}$.

(c) When rival supply chain j's information sharing arrangement is full information sharing, the effect of partial information sharing on retailer i is given by $\Pi^{\mathbf{P}}_{R_i}(\boldsymbol{\phi}^{\mathbf{FP}}_j) - \Pi^{\mathbf{N}}_{R_i}(\boldsymbol{\phi}^{\mathbf{FN}}_j) = \frac{(-\gamma+k+6)^2 m}{(\gamma^2-4(k+6))^2} > 0$ and the effect on the platform is given by $\Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{FP}}_j) + \Pi^{\mathbf{F}}_{P_j}(\boldsymbol{\phi}^{\mathbf{PF}}_i) - [\Pi^{\mathbf{N}}_{P_i}(\boldsymbol{\phi}^{\mathbf{FN}}_j) + \Pi^{\mathbf{F}}_{P_j}(\boldsymbol{\phi}^{\mathbf{NF}}_i)] = \frac{2\left(-\gamma^4+2\gamma^2(k+10)(k+6)-2\gamma(k+10)(k+6)^2+(k+6)^4\right)}{(k+6)^2(\gamma^2-4(k+6))^2}m > 0$.

Furthermore, the effect of full information sharing on retailer i and manufacturer i is given by $\Pi^{\mathbf{F}}_{R_i}(\boldsymbol{\phi}^{\mathbf{FF}}_j) - \Pi^{\mathbf{N}}_{R_i}(\boldsymbol{\phi}^{\mathbf{FN}}_j) = \frac{m}{(\gamma+k+6)^2} > 0$ and $\Pi^{\mathbf{F}}_{M_i}(\boldsymbol{\phi}^{\mathbf{FF}}_j) - \Pi^{\mathbf{N}}_{M_i}(\boldsymbol{\phi}^{\mathbf{FN}}_j) = \frac{(k+4)m}{2(\gamma+k+6)^2} > 0$, respectively, and the effect on the platform is given by $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{FF}}_j) + \Pi^{\mathbf{F}}_{P_j}(\boldsymbol{\phi}^{\mathbf{FF}}_i) - [\Pi^{\mathbf{N}}_{P_i}(\boldsymbol{\phi}^{\mathbf{FN}}_j) + \Pi^{\mathbf{F}}_{P_j}(\boldsymbol{\phi}^{\mathbf{NF}}_i)] = \frac{2m((k+6)^2-\gamma^2-2\gamma(k+6))}{(k+6)^2(\gamma+k+6)^2} > 0$.

The above discussion proves the result. □

B.5. Proof of Proposition 7

We discuss the effect of full information sharing (with a supply chain i) on relevant players as follows.

(a) When the rival supply chain j has partial information sharing, i.e., $\mathbf{Y}_j = \mathbf{P}$, the effect of full information sharing on retailer i is $\Pi^{\mathbf{F}}_{R_i}(\boldsymbol{\phi}^{\mathbf{PF}}_j) - \Pi^{\mathbf{P}}_{R_i}(\boldsymbol{\phi}^{\mathbf{PP}}_j) = -\frac{8(k+2)m(20-\gamma^2+2k)}{(\gamma+4)^2(\gamma^2-4(k+6))^2} < 0$ and the effect on manufacturer i is $\Pi^{\mathbf{F}}_{M_i}(\boldsymbol{\phi}^{\mathbf{PF}}_j) - \Pi^{\mathbf{P}}_{M_i}(\boldsymbol{\phi}^{\mathbf{PP}}_j) = \frac{(k+2)m(\gamma^4-4\gamma^2(k+8)+8k(k+10)+256)}{(\gamma+4)^2(\gamma^2-4(k+6))^2} > 0$. Furthermore, the direct effect of full information sahring on the platform is $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{PF}}_j) - \Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{PP}}_j) = -\frac{16(k+2)m\left(-\gamma^2+2k+20\right)}{(\gamma+4)^2(\gamma^2-4(k+6))^2} < 0$, the side effect on the platform is $\Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{FP}}_i) - \Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{PP}}_i) = \frac{2\gamma(k+2)m(-2(\gamma-1)\gamma+(\gamma+8)k+48)}{(\gamma+4)^2(\gamma^2-4(k+6))^2} > 0$, and the overall effect of full information sharing on the platform is given by: $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{PF}}_j) - \Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{PP}}_j) + \Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{FP}}_i) - \Pi^{\mathbf{P}}_{P_j}(\boldsymbol{\phi}^{\mathbf{PP}}_i) = \frac{2(k+2)m((\gamma(\gamma+8)-16)k-2((\gamma-8)\gamma(\gamma+3)+80))}{(\gamma+4)^2(\gamma^2-4(k+6))^2} < 0$.

(b) When the rival supply chain j has full information sharing, i.e., $\mathbf{Y}_j = \mathbf{F}$, the effect of full information sharing on retailer i is $\Pi^{\mathbf{F}}_{R_i}(\boldsymbol{\phi}^{\mathbf{FF}}_j) - \Pi^{\mathbf{P}}_{R_i}(\boldsymbol{\phi}^{\mathbf{FP}}_j) = -\frac{m(\gamma^4-2\gamma^2(k+6)^2+(k+2)(k+6)^2(k+10))}{16(k+6)^2(\gamma+k+6)^2} < 0$ and the effect on manufacturer i is $\Pi^{\mathbf{F}}_{M_i}(\boldsymbol{\phi}^{\mathbf{FF}}_j)-\Pi^{\mathbf{P}}_{M_i}(\boldsymbol{\phi}^{\mathbf{FP}}_j)=\frac{(k+2)m(2\gamma^4-2\gamma^2(k+6)(k+8)+(k+6)^2(k(k+10)+32))}{2(\gamma+k+6)^2(\gamma^2-4(k+6))^2}>0$. Moreover, the direct effect of full information on the platform is $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{FF}}_j)-\Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{FP}}_j)=-\frac{2(k+2)(k+6)m(60-2\gamma^2+k(k+16))}{(\gamma+k+6)^2(\gamma^2-4(k+6))^2}<0$, the side effect on the platform is $\Pi^{\mathbf{F}}_{P_j}(\boldsymbol{\phi}^{\mathbf{FF}}_i)-\Pi^{\mathbf{F}}_{P_j}(\boldsymbol{\phi}^{\mathbf{PF}}_i)=\frac{2\gamma(k+2)m(2(24-\gamma^2-\gamma)+(8-\gamma)k)}{(\gamma+k+6)^2(\gamma^2-4(k+6))^2}>0$, and the overall effect of full information sharing on the platform is $\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{FF}}_j)-\Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{FP}}_j)+\Pi^{\mathbf{F}}_{P_j}(\boldsymbol{\phi}^{\mathbf{FF}}_i)-\Pi^{\mathbf{F}}_{P_j}(\boldsymbol{\phi}^{\mathbf{PF}}_i)=-\frac{2(k+2)m(2\gamma^3-\gamma^2(k+10)-8\gamma(k+6)+(k+6)^2(k+10))}{(\gamma+k+6)^2(\gamma^2-4(k+6))^2}<0$.

From the above results, we conclude that manufacturer i needs to offer side payments to retailer i and the platform, which are no less than $|\Pi^{\mathbf{F}}_{R_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{F}}_j)-\Pi^{\mathbf{P}}_{R_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{P}}_j)|$ and $|\Pi^{\mathbf{F}}_{P_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{F}}_j)-\Pi^{\mathbf{P}}_{P_i}(\boldsymbol{\phi}^{\mathbf{Y}_j,\mathbf{P}}_j)+\Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}^{\mathbf{F},\mathbf{Y}_j}_i)-\Pi^{\mathbf{Y}_j}_{P_j}(\boldsymbol{\phi}^{\mathbf{P},\mathbf{Y}_j}_i)|$, respectively. Specifically, when rival supply chain j's information arrangement is partial information sharing (i.e., $\mathbf{Y}_j=\mathbf{P}$), manufacturer i's net value of full information sharing, considering the side payments, is given by:

$$\frac{(k+2)m\left(\gamma^4-4\gamma^3-2\gamma^2(k+2)+16\gamma(k+6)+8k(k+4)-224\right)}{(\gamma+4)^2\left(\gamma^2-4(k+6)\right)^2}, \tag{28}$$

which is positive only when $k>\kappa^{\mathbf{P}}=\frac{1}{8}\left(\gamma^2-8\gamma-16+\sqrt{2048-7\gamma^4+16\gamma^3+64\gamma^2-512\gamma}\right)$.

While, when when rival supply chain j's information arrangement is partial information sharing (i.e., $\mathbf{Y}_j=\mathbf{F}$), manufacturer i's net value of full information sharing, considering the side payments, is given by:

$$\frac{1}{16}m\left(-\frac{\gamma^2}{(k+6)^2}+\frac{8(k-8)}{\gamma^2-4(k+6)}+\frac{8(k(k+2)-40)(-2\gamma+k+10)}{\left(\gamma^2-4(k+6)\right)^2}+\frac{2\gamma}{k+6}+\frac{8(k+14)}{(\gamma+k+6)^2}-1\right), \tag{29}$$

which is positive only when $k>\kappa^{\mathbf{F}}$, where $\kappa^{\mathbf{F}}$ is the unique positive root for $f(k)=-\frac{\gamma^2}{(k+6)^2}+\frac{8(k-8)}{\gamma^2-4(k+6)}+\frac{8(k(k+2)-40)(-2\gamma+k+10)}{(\gamma^2-4(k+6))^2}+\frac{2\gamma}{k+6}+\frac{8(k+14)}{(\gamma+k+6)^2}-1=0$. It can verified that $\kappa^{\mathbf{P}}<\kappa^{\mathbf{F}}$, which completes the proof. □

B.6. Proof of Proposition 8

It is easy to verify that $\kappa^{\mathbf{P}}<\kappa^{\mathbf{F}}$. Based on the above conditions, we discuss the platform's equilibrium information sharing strategies for competing supply chains as follows: (1) If $k>\kappa^{\mathbf{F}}$, then a focal supply chain will adopt full information sharing regardless of the rival supply chain's information arrangement. Thus, the unique Nash equilibrium is $(\mathbf{F},\mathbf{F})$; (2) If $\kappa^{\mathbf{P}}\le k\le\kappa^{\mathbf{F}}$, then a focal supply chain will adopt full (resp., partial) information sharing as the rival supply chain adopts partial (resp., full) information sharing. Thus, $(\mathbf{P},\mathbf{F})$ and $(\mathbf{F},\mathbf{P})$ are two possible equilibria; (3) If $k<\kappa^{\mathbf{P}}$, then a focal supply chain will adopt partial information sharing regardless of rival supply chain's information arrangement. Thus, the unique Nash equilibrium is $(\mathbf{P},\mathbf{P})$. The platform's net playoffs under each equilibrium information sharing strategies can be obtained using the results shown in AppendixB.2. □

B.7. Proof of Proposition 9

In this proof, we define $A=a\eta+1$ and use A as the decision variable, rather than a. As a result, the platform's problem becomes

$$\max_{A\ge1}\left\{\frac{4\pi(\ell)^2}{(k+\gamma+6)^2}+\frac{(A-1)\zeta\eta\left(A(\alpha+(2s-r)\ell)^2+2(A-1)\eta\ell^2\right)}{A^2}+\frac{w-Aw}{\eta}\right\},$$

in which $\zeta=\zeta^{\mathbf{FF}}$ if $k>\kappa^{\mathbf{F}}$, $\zeta=\zeta^{\mathbf{FP}}$ if $\kappa^{\mathbf{P}}\le l\le\kappa^{\mathbf{F}}$, and $\zeta=\zeta^{\mathbf{PP}}$ if $k<\kappa^{\mathbf{P}}$. Note that the platform's objective function $G(A,\zeta)=\frac{(A-1)\zeta\eta\left(A(\alpha-r\ell+2s\ell)^2+2(A-1)\eta\ell^2\right)}{A^2}+\frac{w-Aw}{\eta}$ is supermodular, which implies that the optimal solution $A^* = \arg\max_{A \geq 1}\{G(A,\zeta)\}$ is increasing ζ. As such, the optimal accuracy decision $a^{**} = \frac{A^*-1}{\eta}$ is increasing in ζ. From the relationship $\zeta^{\mathbf{FF}} \geq \zeta^{\mathbf{FP}} \geq \zeta^{\mathbf{PP}}$, we obtain $a^{\mathbf{FF}} \geq a^{\mathbf{FP}} \geq a^{\mathbf{PP}}$.

Similarly, the objective function $G(A,\ell)$ is supermodular in (A,ℓ), which implies that A^* is also increasing ℓ. As such, the solutions $\{a^{\mathbf{FF}}, a^{\mathbf{FP}}, a^{\mathbf{PP}}\}$ are all increasing in ℓ.

Finally, it is easy to verify that the parameter $\{\zeta^{\mathbf{FF}}, \zeta^{\mathbf{FP}}, \zeta^{\mathbf{PP}}\}$ are all decreasing in γ, whic implies that A^* is also decreasing in γ. As such, the $\{a^{\mathbf{FF}}, a^{\mathbf{FP}}, a^{\mathbf{PP}}\}$ are all decreasing in ℓ. □

Appendix C: Quantity-dependent Rejection Probability

In this section, we generalize the main model by considering the probability of freight rejection also depends on the retailer's order quantity. There is empirical evidence (e.g., Scott et al. (2017), Acocella (2022) showing that a carrier's probability of freight rejection is increasing as its shippers' loads increase because a larger volume of the shippers' loads enforces the carrier to face the prospect of having too many trucks in a region, resulting in follow-on loads with decreasing profitability. Motivated by the practical evidences, we consider the general probability of freight rejection as follows:

$$\delta(S,q) = g(q) + \ell S,$$

where the term $g(q)$ represents the impact of increasing order quantity on the freight rejection, which is increasing in q. Specifically, we consider a power-form of $g(q)$ as follows:

$$g(q) = \alpha - \lambda/q \text{ for } q > 0,$$

where $\alpha > 0$ and $\lambda > 0$ are two constants. Such power-form function $g(q)$ means that the marginal increase in the probability of freight rejection is diminishing as the volume increases. The diminishing phenomenon has been validated by the empirical work of Scott et al. (2017), which shows that the marginal increase in the probability of freight rejection is 0.0799 as the volume increases from medium to high, while the marginal increase turns into 0.06 as the volume increases from high to very high. The power-from function of $g(q)$ also ensures the tractability of our model.

In this extension, we still follow the definition $\pi := u - c + r(\alpha + s\ell - 1) - s(\alpha + s\ell) - \eta\ell$. We also assume that $\lambda < \frac{\pi(\alpha+s\ell)}{k+4}$ and $0 < \ell < \frac{-2\pi\alpha+\sqrt{(k+4)^2\lambda^2+2\pi(k+8)\lambda+\pi^2}+(k+4)\lambda+\pi}{2\pi s}$ to ensure the equilibrium probability of freight rejection falls into the interval $(0,1)$.

Proposition 10. *In single supply chain with quantity-dependent rejection probability,*

(a) compared to the baseline of no information sharing, partial information sharing benefits the retailer and the platform, but hurts the manufacturer; moreover, full information sharing benefits the manufacturer and the platform, and benefits the retailer iff $\lambda < \frac{(\alpha+s\ell)^2((\alpha+(2s-r)\ell)^2 v_1+\ell^2 v_2)}{2(k+2)v_1\ell(\alpha+(2s-r)\ell)}$.

(b) Compared to partial information sharing, full information sharing benefits the manufacturer, but hurts the retailer and the platform;

(c) Overall, full information sharing needs to be induced by the manufacturer's side payments to the retailer and the manufacturer iff $k > \kappa'$*, where* κ' *is a constant; otherwise, partial information sharing is adopted in the supply chain.*

Proposition 10(a) characterizes the effect of either partial or full information sharing on relevant players relative to the baseline setting of no information sharing. Specifically, partial information sharing benefits the retailer and the platform, but hurts the platform, which is consistent with the finding, shown in Proposition 2, in the main model. While, there is a slight difference lies in the effect of information sharing, that is, full information sharing benefits the retailer iff the parameter λ is not large (i.e., $\lambda < \frac{(\alpha+s\ell)^2(v_1(\alpha+(2s-r)\ell)^2+v_2\ell^2)}{2(k+2)v_1\ell(\alpha+(2s-r)\ell)}$). Since the parameter λ characterizes the sensitivity of freight rejection to the retailer's order quantity, this result means that full information sharing benefits the retailer only when the probability of freight rejection is not highly sensitive to the order quantity.

From Proposition 10(b) and (c), we find that the effect of full information sharing, relative to partial information sharing, is the same as the previous finding in the main model. Furthermore, the condition for adopting full information sharing is that production diseconomy is sufficiently large. As such, we claim that the result for the main model continue to hold in this extension, only when the probability of freight rejection is not highly sensitive to the order quantity.

Proof of Proposition 10. We first consider the baseline setting of on information sharing. Specifically, the retailer maximizes the expected profit, $\mathbb{E}\left[q(u-q-w-r(1-\delta(S,q))-(S+\rho)\delta(S,q))\right]$, with the order quantity:

$$\hat{q}(w,\rho)=\frac{1}{2}(c-\rho(\alpha+s\ell)-w+\pi).$$

Given the conjecture ρ about the wholesale price, the platform maximizes the expected profit, $\mathbb{E}\left[\rho\,\hat{q}(w,\rho)\,\delta(S,\hat{q}(w,\rho))|\Psi\right]$, with the following brokerage fee:

$$\hat{\rho}(w)=\frac{(c-w+\pi)(\alpha+s\ell)-2\lambda}{2(\alpha+s\ell)^2}.$$

Meanwhile, given the conjecture w about the brokerage fee, the manufacturer maximizes the expected profit, $\mathbb{E}\left[\hat{q}(w,\rho)(w-c)-\frac{k}{2}\hat{q}(w,\rho)^2\right]$, with the following wholesale price:

$$\hat{w}(\rho)=c+\frac{(k+2)(\pi-\rho(\alpha+s\ell))}{k+4}.$$

By jointly considering the response functions $\hat{\rho}(w)$ and $\hat{w}(\rho)$, we obtain the equilibrium wholesale price and brokerage fee:

$$\rho^{\mathbf{N}}=\frac{2\pi(\alpha+s\ell)-2(k+4)\lambda}{(k+6)(\alpha+s\ell)^2},w^{\mathbf{N}}=c+\frac{(k+2)(2\lambda+\pi(\alpha+s\ell))}{(k+6)(\alpha+s\ell)},\tag{30}$$

and then the supply chain's equilibrium retail quantity is

$$q^{\mathbf{N}}=\hat{q}(w^{\mathbf{N}},\rho^{\mathbf{N}})=\frac{2\lambda+\pi(\alpha+s\ell)}{(k+6)(\alpha+s\ell)}.\tag{31}$$

Then, the equilibrium probability of freight rejection is $\alpha-\frac{(k+6)\lambda(\alpha+s\ell)}{2\lambda+\pi(\alpha+s\ell)}+s\ell$, which is positive under the assumption $\lambda<\frac{\pi(\alpha+s\ell)}{k+4}$.

Using the equilibrium wholesale price and brokerage fee $\{\rho^{\mathbf{N}},w^{\mathbf{N}}\}$, we obtain the retailer's, manufacturer's, and platform's payoffs in the baseline setting, which are respectively denoted by $\Pi_R^{\mathbf{N}},\Pi_M^{\mathbf{N}},\Pi_P^{\mathbf{N}}$, as follows:

$$\begin{aligned}\Pi_R^{\mathbf{N}}&=\frac{\lambda\left(-2(k(k+10)+22)\lambda-(k+6)^2(r-s)(\alpha+s\ell)^2\right)+2\pi(k+8)\lambda(\alpha+s\ell)+\pi^2(\alpha+s\ell)^2}{(k+6)^2(\alpha+s\ell)^2},\\ \Pi_M^{\mathbf{N}}&=\frac{(k+4)(2\lambda+\pi(\alpha+s\ell))^2}{2(k+6)^2(\alpha+s\ell)^2},\quad \Pi_P^{\mathbf{N}}=\frac{2(\pi(\alpha+s\ell)-(k+4)\lambda)^2}{(k+6)^2(\alpha+s\ell)^2}.\end{aligned}\tag{32}$$

In the case of partial information sharing, the retailer maximizes the expected profit conditioned on Ψ, $\mathbb{E}\left[q(u-q-w-r(1-\delta(S,q))-(S+\rho)\delta(S,q))|\Psi\right]$, with the order quantity:

$$\breve{q}(\rho,w,\Psi)=\frac{1}{2}(c-\alpha(\mathbb{E}\left[\epsilon|\Psi\right]+\rho)+\ell(\mathbb{E}\left[\epsilon|\Psi\right]r-\mathbb{E}\left[\epsilon|\Psi\right](\rho+2s)-\mathbb{E}\left[\epsilon^2|\Psi\right]+\eta-\rho s)-w+\pi).$$

Given the conjecture w about the wholesale price, the platform maximizes the expected profit, $\mathbb{E}\left[\rho\,\hat{q}(w,\rho,\Psi)\,\delta(S,\hat{q}(w,\rho))|\Psi\right]$, with the following brokerage fee:

$$\breve{\rho}(w,\Psi)=\frac{(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))(c-\alpha\mathbb{E}\left[\epsilon|\Psi\right]+\ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s)-\mathbb{E}\left[\epsilon^2|\Psi\right]+\eta)-w+\pi)-2\lambda}{2(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))^2}.$$

Without observing the signal Ψ, the manufacturer maximizes the expected profit based on prior information, $\mathbb{E}\left[\breve{q}(w,\rho,\Psi)(w-c)-\frac{k}{2}\breve{q}(w,\rho,\Psi)^2\right]$, with the following wholesale price:

$$\breve{w}(\rho)=c+\frac{\mathbb{E}\left[(\rho(\Psi)(k(\ell(-\mathbb{E}\left[\epsilon|\Psi\right]-s)-\alpha)-2(\alpha+\mathbb{E}\left[\epsilon|\Psi\right]\ell+s\ell)))\right]+\pi(k+2)}{k+4}.$$

By jointly considering the response functions, we find the Bayesian Nash equilibrium that simultaneously satisfy $\breve{q}(\rho,w,\Psi)$ and $\breve{w}(\rho)$ as follows:

$$\rho^{\mathbf{P}}=\frac{(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))\left(-\alpha\mathbb{E}\left[\epsilon|\Psi\right]+\ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s)-\mathbb{E}\left[\epsilon^2|\Psi\right]+\eta)-\frac{(k+2)((2\lambda+\pi)s\ell-2\lambda)}{(k+6)s\ell}+\pi\right)-2\lambda}{2(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))^2},$$
$$w^{\mathbf{P}}=c+\frac{(k+2)(2\lambda+\pi(\alpha+s\ell))}{(k+6)(\alpha+s\ell)}$$

Again, based on the equilibrium wholesale price and brokerage fee $\{\rho^{\mathbf{P}},w^{\mathbf{P}}\}$ we also compute the all the players' payoffs in the case of partial information, which are respectively denoted by $\Pi_R^{\mathbf{P}},\Pi_M^{\mathbf{P}},\Pi_P^{\mathbf{P}}$. However, the exact expressions for $\{\Pi_R^{\mathbf{P}},\Pi_M^{\mathbf{P}},\Pi_P^{\mathbf{P}}\}$ are very complicated because the term $\mathbb{E}\left[\frac{1}{s+\mathbb{E}[\epsilon|\Psi]}\right]$ does not have closed form expressions. For ease of expositions, we use the following approximation, $s+\mathbb{E}\left[\epsilon|\Psi\right]\approx s$, to simplify the expressions, where the approximation actually makes sense when the variability of ϵ is not large. Then, we have:

$$\begin{aligned}\Pi_R^{\mathbf{P}}&=\Pi_R^{\mathbf{N}}+\frac{1}{16}\left(v_1(\alpha-r\ell+2s\ell)^2+v_2\ell^2\right),\\ \Pi_M^{\mathbf{P}}&=\Pi_M^{\mathbf{N}}-\frac{1}{32}k\left(v_1(\alpha-r\ell+2s\ell)^2+v_2\ell^2\right),\\ \Pi_P^{\mathbf{P}}&=\Pi_P^{\mathbf{N}}+\frac{1}{8}\left(v_1(\alpha-r\ell+2s\ell)^2+v_2\ell^2\right),\end{aligned}\tag{33}$$

Similarly, let $\{w^{\mathbf{F}},\rho^{\mathbf{F}}\}$ denote the equilibrium wholesale price and brokerage fee in the case of full information sharing, and let $\Pi_R^{\mathbf{F}},\Pi_M^{\mathbf{F}},\Pi_P^{\mathbf{F}}$ denote the retailer's, the manufacturer's, and the platform's payoffs. Then we have:

$$\rho^{\mathbf{F}}=\frac{2(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))(-\alpha\mathbb{E}\left[\epsilon|\Psi\right]+\ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s)-\mathbb{E}\left[\epsilon^2|\Psi\right]+\eta)+\pi)-2(k+4)\lambda}{(k+6)(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))^2},$$
$$w^{\mathbf{F}}=c+\frac{(k+2)((\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))(-\alpha\mathbb{E}\left[\epsilon|\Psi\right]+\ell(\mathbb{E}\left[\epsilon|\Psi\right](r-2s)-\mathbb{E}\left[\epsilon^2|\Psi\right]+\eta)+\pi)+2\lambda)}{(k+6)(\alpha+\ell(\mathbb{E}\left[\epsilon|\Psi\right]+s))}$$

and

$$\begin{aligned}\Pi_R^{\mathbf{F}}&=\Pi_R^{\mathbf{N}}+\frac{v_1(\alpha-r\ell+2s\ell)^2+v_2\ell^2}{(k+6)^2}-\frac{2(k+2)v_1\ell(\alpha+(2s-r)\ell)}{(k+6)^2(\alpha+s\ell)^2}\lambda,\\ \Pi_M^{\mathbf{F}}&=\Pi_M^{\mathbf{N}}+\frac{(k+4)\left(v_1(\alpha-r\ell+2s\ell)^2+v_2\ell^2\right)}{2(k+6)^2},\\ \Pi_P^{\mathbf{F}}&=\Pi_P^{\mathbf{N}}+\frac{2\left(v_1(\alpha-r\ell+2s\ell)^2+v_2\ell^2\right)}{(k+6)^2}.\end{aligned}\tag{34}$$

From (33) we find that partial information sharing benefits the retailer and the platform, but hurts the manufacturer relative to no information sharing. Observing (34) we find that full information sharing benefits the retailer and the manufacturer, and benefits the retailer iff $\lambda < \frac{(\alpha+s\ell)^2\left(v_1(\alpha-r\ell+2s\ell)^2+v_2\ell^2\right)}{2(k+2)v_1\ell(\alpha+(2s-r)\ell)}$.

In addition, by comparing (33) and (34), we find that full information sharing hurts the retailer and the platform, and benefits the manufacturer. Hence, it is necessary for the manufacturer to offer side payments the retailer and the platform to induce full information sharing. With the side payment, the manufacturer's net value under full information sharing sharing is given by:

$$\frac{\frac{(k+2)v_1(-\alpha+r\ell-2s\ell)\left((k(k+4)-28)(\alpha+s\ell)^2(-\alpha+r\ell-2s\ell)+64\lambda\ell\right)}{(\alpha+s\ell)^2}+(k(k(k+8)+4)+16)v_2\ell^2}{32(k+6)^2},$$

which is positive when $k > \kappa'$, where κ' is the unique positive root for the above function. $\square$