Forecast Integration in Supply Chains under Freight Rejection

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Freight transportation is a major source of supply chain cost, and one critical challenge is freight rejection, whereby a contract carrier declines a tendered shipment when spot market conditions are favorable. To mitigate this risk, digital freight platforms such as DAT and Uber Freight provide both backup freight and spot rate forecasts. Through API integration, these forecasts can be integrated into supply chains so firms can adjust contract terms and procurement decisions based on anticipated logistics costs. We study the supply chain implications of spot rate forecast integration under freight rejection. We develop a game-theoretic model of a manufacturer, a retailer, and a digital freight platform. We examine how forecast integration affects wholesale pricing, retail ordering, and platform rate decisions, and characterize its value to market participants and the adoption of forecast integration in equilibrium. We find that forecast integration enables the manufacturer to make the wholesale price responsive to the spot rate forecast, which in turn induces a countervailing response from the platform in its freight-rate decision. This platform rate counter-response reduces the retailer's expected shipping cost and leads forecast integration to always benefit the supply chain, although its value to the manufacturer, the retailer, and the platform is more nuanced and depends on the degree of production (dis)economy. In equilibrium, forecast integration is adopted when production exhibits sufficiently strong economy or diseconomy. We further show that mitigating freight rejection by, e.g., cultivating shipper-carrier relationships and improving contract explicitness, can unintentionally reduce retailer and supply chain profits by weakening supply chain responsiveness to spot market conditions, and that this effect can be amplified under forecast integration. We calibrate our model to real-world data and show that forecast integration increases system profit by 2.69% on average and by as much as 25.56%. Our results demonstrate the value of forecast integration in supply chains, provide prescriptive guidance for designing operational decision rules under forecast integration, and highlight how production (dis)economy shapes the value created by forecast integration.

Key words: digital freight platforms, freight rejection, forecast integration, supply chains

1. Introduction

Freight transportation constitutes a major source of supply chain cost. In the U.S., business logistics costs reached \$2.6 trillion in 2024, or 8.7% of GDP, and the trucking industry alone generated about \$906 billion in revenue (AASHTO 2025, ATA 2025). In truckload markets, shippers conduct annual procurement auctions to contract with carriers on specific lanes at prearranged rates for an extended period (e.g., one year). These contracts are binding in price but not in tender/freight acceptance, so when a shipment is tendered to the contracted carrier, the carrier may still reject it (Scott et al. 2020, Babakan et al. 2025). This *freight rejection* becomes more likely when the spot rate, i.e., the freight rate on the open market at the time of shipping, rises, because a higher spot rate increases the carrier's opportunity cost of accepting the load at the contracted rate (Scott et al. 2017, Holm 2020, Uber Freight 2024, Wingfield 2025). Freight rejection is common, ranging from 4% to more than 20% in recent years (Strickland 2025), and is also very costly because rejected shipments must be moved through backup carriers at rates substantially above contracted rates. Scott et al. (2017) empirically observe that spot rates are on average 62% higher than corresponding contract rates, and that freight rejection costs U.S. shippers $5.7 to $11.4 billion annually.

When freight rejection occurs, companies increasingly rely on digital freight platforms, such as DAT, Uber Freight and Amazon Freight, to fulfill the shipment. Through access to broad carrier networks, these platforms help shippers secure backup freight capacity on short notice and reduce the search and coordination frictions associated with last-minute transportation procurement, thereby serving as an important operational buffer against freight rejection. Recent industry guidance likewise indicates that shippers use digital freight platforms as a backup channel when contracted freight is rejected (Cuthrie 2026, Uber Freight 2026b, DAT Freight & Analytics 2026c).

Beyond providing access to last-minute freight capacity, digital freight platforms are also increasingly positioned as logistics data analytics providers (McGann 2025, Gaikwad 2025). Leveraging large-scale and granular data on shipment transactions, major digital freight platforms offer predictive analytics services about spot markets, including lane-level spot rates, which enable shippers to mitigate logistics risks such as freight rejection. For example, DAT's Ratecast, part of DAT iQ RateView, generates lane-level spot rate forecasts that enable better-informed shipment decisions (DAT Freight & Analytics 2026a,b). Moreover, Uber Freight predicts freight rejection using spot rate forecasts and offers predictive analytics services through its integrated analytics platform, Uber Freight Insights AI (Uber Freight 2023, 2025).

In practice, the value of logistics predictive analytics extends beyond the freight market and can influence upstream supply chains. Leading digital freight platforms such as DAT and Uber Freight distribute real-time freight market intelligence including spot rate forecasts through API integrations with transportation management systems (TMS), enterprise resource planning (ERP) systems, and procurement platforms (Uber Freight 2020, DAT Freight & Analytics 2025a,b). By integrating real-time logistics predictive analytics into firms' operations workflows, supply chain participants can automatically adjust contract terms and procurement decisions based on anticipated logistics costs, which are an important component of firms' landed costs (Oracle Supply Chain

& Manufacturing 2026, DHL Express 2025, Armstrong 2025). These logistics analytics services represent an increasingly important revenue stream for digital freight platforms (Gitnux 2026).

In this paper, we examine the supply chain implications of spot rate forecast integration under freight rejection. This problem is highly nontrivial due to intricate strategic interactions among the manufacturer, the retailer, and the digital freight platform that provides the forecast. In particular, forecast integration enables the manufacturer to make the wholesale price responsive to spot market conditions. This, in turn, affects the retailer's ordering decision, which also depends on the spot rate forecast as it provides updated information on the expected shipping cost under freight rejection. These supply chain decisions further shape the platform's freight rate decision, which collectively determine the value of forecast integration to the supply chain and the platform.

To examine these interactions, we develop a game-theoretic model consisting of a supply chain and a digital freight platform ("it"). In the supply chain, a retailer ("she") procures products from a manufacturer ("he") under a wholesale pricing contract and sells them in a market with linear inverse demand. To deliver the products, the retailer first uses a contract carrier, who may reject the shipment with a probability that increases in the spot rate. When freight rejection occurs, the retailer uses the digital freight platform for shipment. The platform sets the freight rate charged to the retailer and incurs a shipping cost that also increases with the spot rate. The spot rate is uncertain, and the platform holds a forecast of it. The retailer observes this forecast and adjusts her order quantity accordingly. If the platform enables forecast integration across the supply chain, the manufacturer also observes the forecast and can make the wholesale price responsive to it. We derive the equilibrium wholesale price, order quantity, and platform freight rate, and characterize the value of forecast integration for each market participant as well as its adoption in equilibrium.

1.1. Main Findings

Forecast integration enables the manufacturer to make the wholesale price responsive to the spot rate forecast, which in turn reshapes the retailer's order quantity and the platform's freight-rate decision. In particular, this responsive wholesale pricing induces a countervailing response from the platform: it adjusts the freight rate in the opposite direction so as to offset the effect of the wholesale price on the retailer's order quantity. Consequently, forecast integration can make the retailer's order quantity either less or more responsive to spot market conditions, depending on the degree of production (dis)economy. We further show that the optimal wholesale pricing, retail quantity, and platform freight rate decisions depend not only on the posterior mean of the spot rate but also on the posterior second moment, which provides updated information about the platform's expected shipping cost. These results complement the literature which shows that sharing demand information with the manufacturer makes the retail quantity less responsive and that supply chain decisions depend on the posterior mean (but not second moment) of market size.

Next, we analyze the value of forecast integration for each market participant. We show that forecast integration always benefits the supply chain, regardless of the degree of production economy or diseconomy. However, its value to the manufacturer, the retailer, and the platform is more nuanced. When production exhibits weak economy or diseconomy, forecast integration benefits the manufacturer but hurts the retailer and the platform. In contrast, when production exhibits strong economy, it benefits the retailer and the platform but hurts the manufacturer. We identify a novel mechanism underlying these results: responsive wholesale pricing can lower the retailer's expected shipping cost by inducing platform rate counter-response. This leads forecast integration to always benefit the supply chain for any production (dis)economy level, which contrasts to the literature showing that sharing demand information upstream benefits the supply chain only under strong production diseconomy.

We then characterize the equilibrium adoption of forecast integration and show that it is adopted when production exhibits sufficiently strong diseconomy or strong economy. Interestingly, mitigating production diseconomy, which lowers the production cost, can reduce the platform's equilibrium net profit despite increasing the manufacturer's and the retailer's net profits. This occurs because, under strong production diseconomy, the manufacturer uses responsive wholesale pricing to dampen order quantity variability, which further lowers the expected shipping cost. Mitigating production diseconomy reduces this benefit and may hurt the platform.

We further examine the impact of freight rejection mitigation by, e.g., cultivating shipper-carrier relationships. Such mitigation first decreases and then increases retailer and supply chain profits. Moreover, forecast integration amplifies the range over which freight rejection mitigation reduces supply chain profit, and can amplify or shrink the range for reducing retailer profit, depending on the production (dis)economy level. Next, we extend the model to competitive supply chains and show that forecast integration is adopted in more cases as competition intensifies. Finally, we calibrate our model to real-world data and quantify the value of forecast integration as 2.69% of system profit on average and as much as 25.56%.

1.2. Related Literature

Digital freight platforms have attracted growing research interest in operations management recently. Existing studies focus on the role of these platforms in addressing matching and assignment problems (Caplice 2007, Min and Kang 2021). Miller et al. (2020) examine truck routing problems for digital freight platforms in a Markov decision process. Li et al. (2020) study the joint optimization of matching and pricing strategies for deliveries to multiple retailers. Zhou and Wan (2022) empirically investigate how platforms affect the profitability and stock performance of incumbent road freight logistics companies. Our paper contributes to this literature by examining supply chain implications of forecast integration from digital freight platforms.

A substantial body of operations management literature examines freight operations in supply chain logistics, focusing on the interplay between freight operations and classical retail, inventory, and production decisions (Lu et al. 2017, 2020, Boada-Collado et al. 2020). The majority of this literature assumes that shippers secure guaranteed freight rates with contract carriers and ignores freight rejection, which entails substantial costs for supply chains. A growing number of researchers have begun to explore freight operations in the presence of freight rejection. Tsai et al. (2011) propose the use of derivative contracts in trucking as a hedging mechanism against uncertainty in transportation capacity and cost. Scott et al. (2017) empirically identify the key operational and economic factors that drive or deter freight rejection, and recommend adopting a flexible freight pricing mechanism as a mitigating measure.

Our paper is also related to the extensive literature on information sharing in supply chains (Li 2002, Ha et al. 2011, Huang et al. 2018, Ha et al. 2022, Li and Zhang 2023). Our paper is more closely related to papers that examine information sharing by platforms. Liu et al. (2021) consider 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. Ha et al. (2022) develop 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. Our paper contributes to this literature by examining the dual roles of digital freight platforms as backup freight and logistics analytics providers for supply chains under forecast integration.

1.3. Paper Organization

The remainder of this paper is organized as follows. Section 2 presents the model setup. Section 3 develops the analytical results for the main model and Section 4 provides several additional considerations. Section 5 generalizes the analysis to a setting with competing supply chains. Section 6 provides concluding remarks. Proofs of all results are relegated to the E-Companion.

2. Model

We consider a sequential game in which a retailer orders q units of a product from a manufacturer at wholesale price w and sells in a market at price $p=a-q$ per unit, where a denotes the market size. To deliver the product to the market, the retailer uses a contract carrier at pre-determined freight rate r_C per unit of product. We treat r_C as exogenous because contracted freight rates are typically established prior to the selling season through annual procurement auctions and remain fixed during the selling season (Caplice 2007, Scott et al. 2017, Emadikhiav and Day 2025).

Spot market: Although the contracted freight rate r_C is fixed, the freight rate on the open market at the time of shipping (the spot rate, hereafter) is uncertain as it depends on contemporaneous freight market conditions, including demand-supply imbalance, fuel costs, weather, and lane-level congestion (Freightify 2024, FreightRate 2025). When the spot rate is high, contract carriers have strong incentives to reject shipment tenders; truckload freight contracts are typically nonbinding with respect to tender/freight acceptance (Scott et al. 2020, Babakan et al. 2025). Freight rejections are common—the national Outbound Tender Rejection Index ranges between 4% to more than 20% in recent years (Strickland 2025)—and are very costly to shippers (Scott et al. 2017).

We model the spot rate as $S = s + \epsilon$ per unit of product, where s is the mean and ϵ is a zero-mean random noise with variance σ^2. At the time of shipping, the retailer first tenders the shipment to the contract carrier, who rejects the freight with probability $\delta(S)$. Since a higher spot rate S increases the contract carrier's opportunity cost of accepting the tender, the freight rejection probability $\delta(S)$ increases in S, as well documented empirically (Uber Freight 2024, Wingfield 2025, Holm 2020). To capture this parsimoniously, we consider a linear freight rejection function $\delta(S) = \alpha + \beta S$, where $\beta > 0$, to obtain clear and analytical insights. Our structural results continue to hold for realistic freight rejection functions calibrated to real-world data; see Section 4.3. We assume $s > r_C$, i.e., the spot rate is on average higher than the contracted rate, to focus on a tight market where freight rejection is salient. Scott et al. (2017) empirically observe that spot prices are on average 62% higher than their corresponding contract rates.

When freight rejection occurs, the retailer uses a digital freight platform (e.g., Amazon Freight, DAT, and Uber Freight) to ship the product. The platform charges the retailer a platform (freight) rate r per unit of product and pays a platform carrier $\kappa(S)$ per unit of product for the shipment. Since this transaction competes closely with the spot market for truck capacity, the platform's per-unit shipping cost $\kappa(S)$ is increasing in the spot rate S (Amazon Relay 2026, Uber Freight 2026a). We model this parsimoniously as $\kappa(S) = v + \rho S$, where $\rho \geqslant 0$. In Section 4.3, we calibrate our model to real-world data and show that this linear specification provides a good fit to data.

Spot rate forecast: We incorporate the platform's role as a logistics analytics provider by considering that, before the spot rate is realized, the platform obtains a forecast (e.g., based on historical transaction data) and shares it with the retailer for free.[1] Specifically, we assume that the platform obtains an unbiased estimator of ϵ (i.e., the random component of spot rate S), as denoted by ξ, in a linear expectation information structure[2] such that the posterior forecast of ϵ conditional on ξ, has mean

$$\mathrm{E}_\epsilon[\epsilon \mid \xi] = \frac{\tau}{1/\sigma^2 + \tau}\xi, \tag{1}$$

[1] Even absent such information sharing, the retailer can infer the platform's spot rate forecast from the optimal platform freight rate; see below.

[2] The linear expectation information structure, including well-known conjugate pairs such as Normal-Normal, Beta-Binomial, and Gamma-Poisson, means the conditional expectation of ϵ given signal ξ is a linear combination of the signal and the expectation of ϵ which is zero.

where $\tau := 1/\mathtt{E}_\epsilon[\mathtt{Var}_\xi[\xi \mid \epsilon]]$ represents the informativeness of signal ξ, with higher τ indicating more informativeness. It is straightforward to verify that $\mathtt{E}_\xi[\mathtt{E}_\epsilon[\epsilon \mid \xi]] = 0$ due to unbiasedness and $\mathtt{Var}_\xi[\mathtt{E}_\epsilon[\epsilon \mid \xi]] = \tau\sigma^4/(1+\tau\sigma^2)$ is increasing in τ. This is because, with increased informativeness τ, the signal ξ enters the posterior $\mathtt{E}_\epsilon[\epsilon \mid \xi]$ with a larger weight by (1), which increases posterior variability because the signal ξ is *ex ante* uncertain. This information structure has been widely adopted in the supply chain management literature on information sharing (Ha et al. 2011, Kurtuluş et al. 2012, Shang et al. 2016, Ha et al. 2017). To ease exposition, we denote $\hat{S} = s + \xi$ and refer to it as the spot rate forecast.

Sequence of events (no forecast integration): We proceed by describing the sequence of events as illustrated in Figure 1. First, without observing spot rate S or forecast $\hat{S}$, the manufacturer sets the wholesale price w and the platform sets a pricing rule $r(\hat{S})$ that specifies the platform freight rate for each possible realization of the spot rate forecast. Second, the spot rate forecast $\hat{S}$ is realized and observed by all market participants. Third, the retailer sets the order quantity q. Fourth, the spot rate S is realized. With probability $1-\delta(S)$, the retailer ships the product through the contract carrier at rate r_C. With probability $\delta(S)$, the contract carrier rejects the shipment, which is fulfilled through the platform at freight rate $r(\hat{S})$. For expositional convenience, we henceforth refer to the manufacturer as "he," the retailer as "she," and the platform as "it."

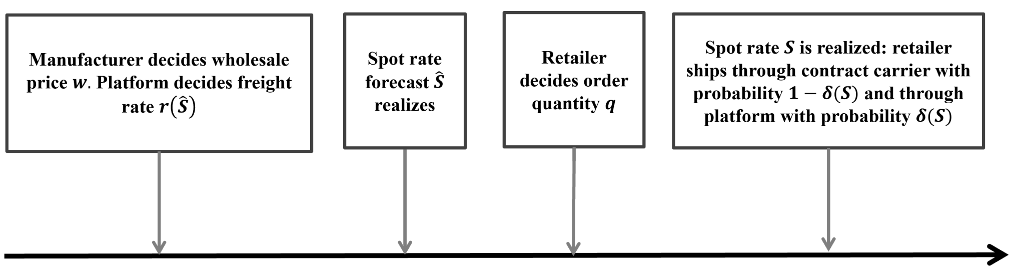


Figure 1 **Sequence of events (no forecast integration)**

We consider the platform to set a freight rate pricing rule based on the spot rate forecast. In practice, major digital freight platforms dynamically adjust shipping quotes based on real-time spot rate forecasts (McGann 2025, Uber Freight 2026a, Project44 2026). We model the manufacturer and the platform as making simultaneous decisions because each chooses its decision without observing the other's. Specifically, the platform does not observe the wholesale price when setting the freight-rate pricing rule because supply chain contracts are private to the manufacturer and the retailer. Likewise, the manufacturer does not observe the platform's pricing rule when setting the wholesale price because the platform's pricing policy is proprietary. Accordingly, in Stage 1, the platform sets $r(\hat{S})$ based on a belief about the wholesale price, denoted by $\hat{w}$, and the manufacturer sets w

based on a belief about the platform's pricing rule, denoted by $\hat{r}(\hat{S})$. See Ha et al. (2011), Shang et al. (2016), and Ha et al. (2017) for similar formulations.

We now formulate the problems of all market participants, starting with the retailer. For any given wholesale price w and platform rate r, the retailer updates belief over spot rate S using forecast $\hat{S}$, and then chooses order quantity $q \geq 0$ to maximize the expected profit

$$\Pi_R(w, r, q \mid \hat{S}) = \mathtt{E}_S[q\,(a - q - w - \delta(S)r - (1-\delta(S))r_C) \mid \hat{S}]. \tag{2}$$

The retailer's profit is equal to the order quantity q multiplied by the profit margin $a - q - w$ net of expected shipping cost $\delta(S)r + (1-\delta(S))r_C$. Let $\tilde{q}(w, r, \hat{S})$ denote the optimal order quantity.

Anticipating the retailer's order quantity $\tilde{q}(w, r, \hat{S})$, the platform sets freight rate $r \geq 0$ for each forecast $\hat{S}$ based on wholesale price belief $\hat{w}$ to maximize the expected profit

$$\Pi_P(r \mid \hat{w}, \hat{S}) = \mathtt{E}_S[\delta(S)(r - \kappa(S))\tilde{q}(\hat{w}, r, \hat{S}) \mid \hat{S}]. \tag{3}$$

The platform's profit is equal to the probability of freight rejection (i.e., the retailer ships through the platform) multiplied by the platform's profit margin $(r - \kappa(S))$ and the shipping quantity $\tilde{q}(\hat{w}, r, \hat{S})$. We use $\tilde{r}(\hat{w}, \hat{S})$ to denote the platform's optimal pricing rule of the freight rate.

We now formulate the manufacturer's wholesale pricing decision for a given belief over platform rate pricing rule $\hat{r}(\hat{S})$. The manufacturer sets $w \geq 0$ to maximize expected profit, where expectation is taken first over spot rate S conditional on each realized forecast $\hat{S}$, and then over forecast $\hat{S}$:

$$\Pi_M(w \mid \hat{r}) = \mathtt{E}_{\hat{S}}[\mathtt{E}_S[(w - C(\tilde{q}(w, \hat{r}(\hat{S}), \hat{S})))\tilde{q}(w, \hat{r}(\hat{S}), \hat{S}) \mid \hat{S}]], \tag{4}$$

where $C(q)$ is the production cost function specified in (6) below. We use $\tilde{w}(\hat{r})$ to denote the optimal wholesale price, suppressing the functional dependence of the manufacturer's belief $\hat{r}(\cdot)$ for notational simplicity. We will characterize the Perfect Bayesian equilibrium of the game denoted by $(w^*, r^*(\cdot))$, which induces consistent decisions and beliefs, i.e., $w^* = \tilde{w}(r^*)$ and $r^*(\cdot) = \tilde{r}(\cdot, w^*)$; see Fudenberg and Tirole (1991) and Ha et al. (2011).

Forecast integration: In the sequential game described above, the spot rate forecast affects the freight market by shaping the platform's freight rate and the retailer's order quantity decisions. In practice, the value of logistics predictive analytics extends beyond the freight market and can influence upstream supply chains. As discussed in Section 1, leading digital freight platforms distribute spot rate forecasts through API integration so supply chain participants can automatically adjust contract terms and procurement decisions based on anticipated logistics costs.

To examine supply chain implications of forecast integration, we consider an alternative setting in which the spot rate forecast is shared across the supply chain, so the wholesale price can be made contingent on the forecast. The sequence of events is as follows (see Figure 2). First, the platform sets price P charged to the retailer for enabling API access of spot rate forecast across the supply chain. Second, the manufacturer offers a transfer payment T to the retailer for adopting forecast integration, so that the wholesale price can be automatically adjusted based on the spot rate forecast. Third, the retailer decides whether to adopt forecast integration. If not, the game proceeds as in Figure 1. If the retailer adopts forecast integration, then the manufacturer and the platform simultaneously decide the pricing rules for wholesale price and platform rate, as denoted by $w(\hat{S})$ and $r(\hat{S})$, respectively. Next, the spot rate forecast $\hat{S}$ is realized and observed by all market participants. The retailer then chooses order quantity q. Finally, the spot rate S is realized and the retailer ships through the contract carrier (platform) if freight rejection does not occur (occurs). For expositional convenience, we refer to this setting as the *Forecast Integration* case, denoted by superscript $\mathtt{I}$, and the benchmark setting illustrated in Figure 1 as the *No Forecast Integration* case, denoted by superscript $\mathtt{N}$.

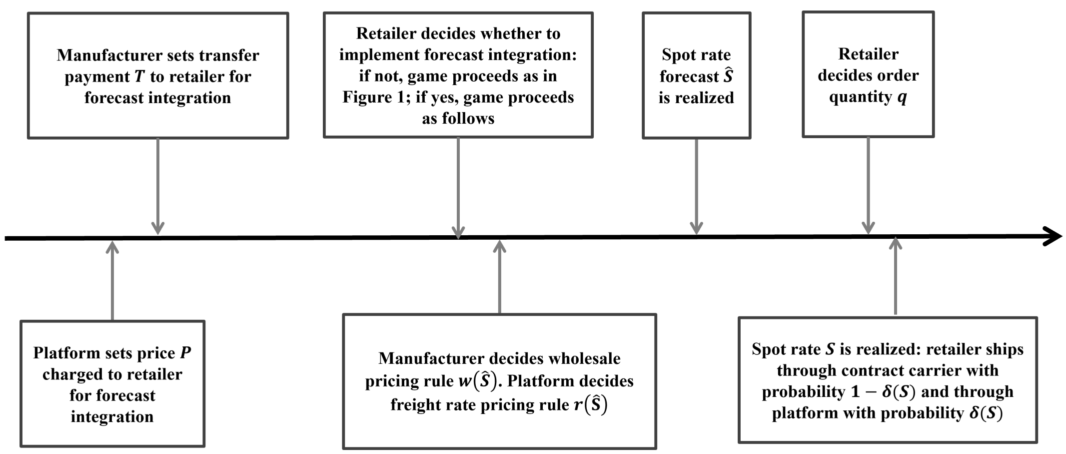


Figure 2 **Sequence of events (forecast integration)**

We now formulate the problems of all market participants. For any given wholesale price w and platform rate r, the retailer's problem is unchanged, as defined in (2), and the optimal order quantity is $\tilde{q}(w,r,\hat{S})$. Anticipating the retailer's optimal order quantity, the platform sets freight rate $r \geq 0$ for each spot rate forecast $\hat{S}$ and given wholesale price belief $\hat{w}(\hat{S})$, to maximize profit $\Pi_P(r \mid \hat{w}(\hat{S}),\hat{S})$ given by (3); the optimal freight rate is $\tilde{r}(\hat{S},\hat{w}(\hat{S}))$. Similarly, the manufacturer sets wholesale price $w \geq 0$ for each given freight rate belief $\hat{r}(\hat{S})$ to maximize expected profit

$$\Pi_M^{\mathtt{I}}(w \mid \hat{r},\hat{S}) = \mathtt{E}_S[(w - C(\tilde{q}(w,\hat{r}(\hat{S}),\hat{S})))\tilde{q}(w,\hat{r}(\hat{S}),\hat{S}) \mid \hat{S}]. \quad (5)$$

Unlike the No (Forecast) Integration case, where the manufacturer sets a fixed wholesale price independent of spot rate forecast (see (4)), in the (Forecast) Integration case, the manufacturer sets a wholesale pricing rule that specifies the optimal wholesale price for each given spot rate forecast $\hat{S}$ to maximize profit $\Pi^{\mathtt{I}}_M(w \mid \hat{r}, \hat{S})$. We use $\tilde{w}^{\mathtt{I}}(\hat{S}, \hat{r})$ to denote the optimal wholesale pricing rule. We will characterize the Perfect Bayesian equilibrium denoted by $(w^{\mathtt{I}*}(\cdot), r^{\mathtt{I}*}(\cdot))$, which induces consistent decisions and beliefs, i.e., $w^{\mathtt{I}*}(\hat{S}) = \tilde{w}^{\mathtt{I}}(\hat{S}, r^{\mathtt{I}*})$ and $r^{\mathtt{I}*}(\hat{S}) = \tilde{r}(\hat{S}, w^{\mathtt{I}*}(\hat{S}))$ for all $\hat{S}$.

Now we consider the first three stages of the game in which the platform sets access price P, the manufacturer sets transfer payment T, and the retailer decides whether to adopt forecast integration. Let $\Pi^{\mathtt{I}}_M$, $\Pi^{\mathtt{I}}_R$, and $\Pi^{\mathtt{I}}_P$ denote the equilibrium profits of the manufacturer, retailer, and platform, respectively, in the continuation game following the retailer's adoption of forecast integration; thus these profits do not include P and T. Similarly, let $\Pi^{\mathtt{N}}_M$, $\Pi^{\mathtt{N}}_R$, and $\Pi^{\mathtt{N}}_P$ denote the corresponding profits in the continuation game when forecast integration is not adopted, as represented in Figure 1. To ease exposition, let $V_R = \Pi^{\mathtt{I}}_R - \Pi^{\mathtt{N}}_R$, $V_M = \Pi^{\mathtt{I}}_M - \Pi^{\mathtt{N}}_M$, and $V_P = \Pi^{\mathtt{I}}_P - \Pi^{\mathtt{N}}_P$ denote, respectively, the gross value of forecast integration to the retailer, the manufacturer, and the platform, before accounting for access price P and transfer payment T.

Under any given access price P paid to the platform and transfer payment T from the manufacturer, the retailer obtains net profit $\Pi^{\mathtt{I}}_R + T - P$ from adopting forecast integration and obtains net profit $\Pi^{\mathtt{N}}_R$ from no adoption. Thus, she should adopt if and only if (iff) $\Pi^{\mathtt{I}}_R + T - P \geq \Pi^{\mathtt{N}}_R$ or equivalently $T \geq P - V_R$. This further suggests that, the manufacturer either sets $T < P - V_R$ to induce no adoption and obtain net profit $\Pi^{\mathtt{N}}_M$, or sets $T \geq P - V_R$ to induce adoption and obtain net profit $\Pi^{\mathtt{I}}_M - T$. It then yields the manufacturer's optimal transfer payment as follows. When $V_M + V_R \geq P$, the manufacturer should set $T = P - V_R$ to induce adoption. In this case, the manufacturer obtains net profit $\Pi^{\mathtt{I}}_M - P + V_R$ and the retailer obtains net profit $\Pi^{\mathtt{N}}_R$. When $V_M + V_R < P$, the manufacturer should set any $T < P - V_R$ to induce no adoption. In this case, the manufacturer obtains net profit $\Pi^{\mathtt{N}}_M$ and the retailer obtains net profit $\Pi^{\mathtt{N}}_R$. Anticipating this, the platform either sets $P \leq V_R + V_M$ to induce adoption and the platform obtains net profit $\Pi^{\mathtt{I}}_P + P$, or sets $P > V_R + V_M$ to induce no adoption and the platform obtains net profit $\Pi^{\mathtt{N}}_P$. It then follows that, the platform should set $P = V_R + V_M$ to induce adoption when $V_P + V_R + V_M \geq 0$, and otherwise should set any $P > V_R + V_M$ to induce no adoption. In Section 3, we continue the analysis by deriving explicit profit expressions and characterizing the equilibrium adoption of forecast integration.

We allow negative transfer payment T to accommodate a general setting where the retailer may pay or charge the manufacturer for adopting forecast integration.[3] A positive T captures the case in which the manufacturer compensates the retailer for implementing the integration and sharing the forecast, whereas a negative T captures the case in which the retailer compensates the manufacturer for automating the wholesale price contingent on the spot rate forecast. As we

[3] We restrict attention to a positive access price, i.e., $P > 0$, without loss of generality. Even if a negative access price were allowed, we find that it would never emerge in equilibrium.

show later, either case can arise in equilibrium, which offers richer insights into the supply chain implications of forecast integration.

Production cost: We model the manufacturer's production cost as

$$C(q) = cq + k\frac{q^2}{2}, \tag{6}$$

where $c > 0$ is the constant marginal cost component and $k > 0$ (resp. $k < 0$) captures production diseconomy (resp. economy). When $k > 0$, production exhibits diseconomy as the marginal cost is increasing in production quantity, i.e., $C''(q) = k > 0$. This occurs when greater production requires more expensive production capacity or input (Ha et al. 2011). When $k < 0$, production exhibits economy as the marginal cost is decreasing in quantity, i.e., $C''(q) = k < 0$. This occurs when there is a learning effect in production or a more efficient technology can be used with a larger production volume (Shang et al. 2016). When $k < 0$, we focus on the non-trivial cases of $q < -c/k$ such that the marginal cost of production is positive, i.e., $C'(q) = c + kq > 0$ iff $q < -c/k$. This quadratic production cost formulation is widely adopted in the supply chain management literature on information sharing (see, e.g., Eliashberg and Steinberg 1991, Anand and Mendelson 1997, Ha et al. 2011, Shang et al. 2016).

We also make the following assumptions. Define $u := a - \mathtt{E}_S[r_C(1-\delta(S)) + \kappa(S)\delta(S)] = a - \beta\rho\sigma^2 - r_C - (\alpha + \beta s)(v + \rho s - r_C)$ as the effective market size net of the expected freight cost. We assume that $u > c$, which requires the supply chain to be efficient at the margin for the first unit. In other words, the marginal benefit from selling the first unit, given by a, exceeds the associated marginal production cost c plus the expected shipping cost $\mathtt{E}_S[r_C(1-\delta(S)) + \kappa(S)\delta(S)]$. We also assume that $k > -4$, i.e., production economy is not too strong. Otherwise, the manufacturer's profit is convex in quantity so he produces either zero or the maximum feasible quantity, which would trivialize the analysis. Finally, we assume that the platform's shipping cost is higher on average than that of the contract carrier, i.e., $\mathtt{E}_S[\kappa(S)] = v + \rho s > r_C$; thus freight rejection raises the expected shipping cost. This assumption is realistic because the platform serves as a backup source of freight capacity that is more closely tied to spot-market conditions. All assumptions are satisfied under our numerical calibration using real-world data; see Section 4.3. We summarize our notation in Table 1 below.

3. Analysis

In this section, we analyze the main model described in Section 2. In Section 3.1, we present and compare equilibrium decisions with vs. without forecast integration. In Section 3.2, we compare the associated profits of all market participants to obtain the value of forecast integration. Next, we analyze the equilibrium adoption of forecast integration in Section 3.3, and examine the profit implications of freight rejection mitigation in Section 3.4. To simplify notation, we suppress subscripts on the expectation and variance operators when the underlying random variable is clear from the context.

Table 1 Summary of Notation

Notation	Definition
a	market size
p	product selling price, given by $p=a-q$
r	platform's freight rate
r_C	contract carrier's freight rate
w	manufacturer's wholesale price
q	retailer's order quantity
S	spot rate, given by $S=s+\epsilon$, where s is the mean and ϵ is zero-mean random noise with variance σ^2
ξ	unbiased estimator of ϵ
τ	defined as $1/\mathtt{E}_\epsilon[\mathtt{Var}_\xi[\xi \mid \epsilon]]$ to represent informativeness of ξ
$\hat{S}$	spot rate forecast, given by $\hat{S}=s+\xi$
$\delta(S)$	freight rejection probability, given by $\delta(S)=\alpha+\beta S$
$\kappa(S)$	platform's per-unit shipping cost, given by $\kappa(S)=v+\rho S$
$C(q)$	production cost, given by $C(q)=cq+kq^2/2$
P	platform's access price for forecast integration
T	manufacturer's transfer payment to retailer for forecast integration
$\Pi_M^{\mathtt{N}}$, $\Pi_R^{\mathtt{N}}$, $\Pi_P^{\mathtt{N}}$	manufacturer's, retailer's, and platform's profits in the continuation game when forecast integration is not adopted
$\Pi_M^{\mathtt{I}}$, $\Pi_R^{\mathtt{I}}$, $\Pi_P^{\mathtt{I}}$	manufacturer's, retailer's, and platform's profits in the continuation game when forecast integration is adopted
V_M, V_R, V_P	value of forecast integration to the manufacturer, the retailer, and the platform

3.1. Equilibrium Decisions

For each of the two cases, with and without forecast integration, we first solve for the optimal decisions of the retailer, the platform, the manufacturer, and then derive the equilibrium decisions and profits; see Section EC.1.1 in the E-Companion for detailed analysis. Here, we present the equilibrium outcomes for the two cases separately. In the next subsection, we compare the equilibrium profits with vs. without forecast integration to characterize its value for each market participant.

Without forecast integration, the equilibrium wholesale price is $w^{\mathtt{N}}=\frac{(k+2)u+4c}{k+6}$, which is independent of the spot rate forecast. The platform's and the retailer's equilibrium decisions are:

$$r^{\mathtt{N}}\,\mathtt{E}[\delta(S)\mid\xi]=\frac{2(u-c)}{k+6}+\mathtt{E}[\delta(S)\kappa(S)]+\frac{\rho(\alpha+2\beta s)+\beta(r_C+v)}{2}\mathtt{E}[\epsilon\mid\xi]+\frac{\beta\rho\left(\mathtt{E}[\epsilon^2\mid\xi]-\sigma^2\right)}{2},\tag{7}$$

$$q^{\mathtt{N}}=\frac{u-c}{k+6}-\frac{\beta\left(v+\rho s-r_C\right)+\rho\left(\alpha+\beta s\right)}{4}\mathtt{E}[\epsilon\mid\xi]-\frac{\beta\rho\left(\mathtt{E}[\epsilon^2\mid\xi]-\sigma^2\right)}{4},\tag{8}$$

where we express the platform decision as the effective freight rate, defined as the actual rate $r^{\mathtt{N}}$ multiplied by the updated (based on forecast) probability of platform shipping $\mathtt{E}[\delta(S)\mid\xi]$, and

$$\mathtt{E}[\epsilon\mid\xi]=\frac{\tau}{1/\sigma^2+\tau}\xi \text{ and } \mathtt{E}[\epsilon^2\mid\xi]=\frac{1}{1/\sigma^2+\tau}+\left(\frac{\tau}{1/\sigma^2+\tau}\right)^2\xi^2\tag{9}$$

are posterior mean and second moment of spot rate's random component ϵ updated by the forecast outcome captured by ξ; other terms do not depend on the spot rate forecast. A higher spot rate forecast $\hat{S} = s + \xi$ indicates a higher expected spot rate $S = s + \mathtt{E}[\epsilon \mid \xi]$. This increases the probability of platform shipping $\delta(S)$ and platform cost $\kappa(S)$. Therefore, the platform raises the effective freight rate and the retailer orders less, i.e., $r^{\mathtt{N}}\,\mathtt{E}[\delta(S) \mid \xi]$ and $q^{\mathtt{N}}$ in (7)-(8) are increasing in $\mathtt{E}[\epsilon \mid \xi]$.

The spot rate forecast also updates beliefs about the squared magnitude of the spot rate's random component $\mathtt{E}[\epsilon^2 \mid \xi]$, which further affects the equilibrium decisions. By (9), a larger absolute value of ξ implies a larger $\mathtt{E}[\epsilon^2 \mid \xi]$. This induces the platform to raise the effective freight rate, since a higher expected magnitude of spot rate randomness increases the platform's expected freight cost. To see this more clearly, note that the effective per-unit shipping cost of the platform, i.e., $\delta(S)\kappa(S)$, is convex and increasing in the spot rate S because a higher S increases both the probability of shipping through the more expensive platform carrier and carrier's rate. By Jensen's inequality, this convexity implies that greater spot rate deviation from the mean increases the expected shipping cost. Accordingly, the platform raises the freight rate and the retailer orders less.

With forecast integration, the equilibrium decisions are given by:

$$w^{\mathtt{I}} = \frac{4c + (k+2)u}{k+6} - \frac{(k+2)(\beta(v + \rho s - r_C) + \rho(\alpha + \beta s))}{k+6}\mathtt{E}[\epsilon \mid \xi] - \frac{(k+2)\beta\rho(\mathtt{E}[\epsilon^2 \mid \xi] - \sigma^2)}{k+6}, \quad (10)$$

$$r^{\mathtt{I}}\,\mathtt{E}[\delta(S) \mid \xi] = \frac{2(u-c)}{k+6} + \mathtt{E}[\delta(S)\kappa(S)] + \frac{(k+4)(\rho(\alpha + 2\beta s) + \beta v) + 2\beta r_C}{k+6}\mathtt{E}[\epsilon \mid \xi] + \frac{(k+4)\beta\rho(\mathtt{E}[\epsilon^2 \mid \xi] - \sigma^2)}{k+6}, \quad (11)$$

$$q^{\mathtt{I}} = \frac{u-c}{k+6} - \frac{\beta(v + \rho s - r_C) + \rho(\alpha + \beta s)}{k+6}\mathtt{E}[\epsilon \mid \xi] - \frac{\beta\rho(\mathtt{E}[\epsilon^2 \mid \xi] - \sigma^2)}{k+6}. \quad (12)$$

Forecast integration leads the wholesale price to adjust based on the spot rate forecast, which further affects the effective platform rate and the retailer's order quantity, as analyzed below.

Proposition 1. *(i) Wholesale price $w^{\mathtt{I}}$ is decreasing in the posterior mean $\mathtt{E}[\epsilon \mid \xi]$ when $k > -2$, and is increasing in $\mathtt{E}[\epsilon \mid \xi]$ when $k < -2$.*

(ii) Effective platform rate $r^{\mathtt{I}}\mathtt{E}[\delta(S) \mid \xi]$ is increasing in the posterior mean $\mathtt{E}[\epsilon \mid \xi]$, as in the case without forecast integration, but is more responsive when $k > -2$ and less responsive when $k < -2$.

(iii) Order quantity $q^{\mathtt{I}}$ is decreasing in the posterior mean $\mathtt{E}[\epsilon \mid \xi]$, as in the case without forecast integration, but is less responsive when $k > -2$ and more responsive when $k < -2$.

Forecast integration enables the manufacturer to make the wholesale price responsive to the posterior mean of the spot rate. When production exhibits strong economy (i.e., $k < -2$), a higher (resp. lower) posterior mean of the spot rate leads the manufacturer to raise (resp. lower) the wholesale price. This amplifies the variability of the retailer's order quantity, thereby reducing the expected production cost. In contrast, when production exhibits weak economy or diseconomy (i.e.,

$k > -2$), the wholesale price responds in the opposite direction. This enables the manufacturer to extract greater surplus, e.g., by charging a higher wholesale price when the forecast is low and the retailer's order quantity is high. The responsive wholesale price also dampens variability of the order quantity, which lowers the expected production cost under diseconomy. These mechanisms are similar in spirit to demand information sharing in Ha et al. (2011) and Shang et al. (2016).

Interestingly, the manufacturer's responsive wholesale pricing induces a countervailing response from the platform. Although the effective platform rate remains increasing in the posterior mean of the spot rate, it becomes more responsive when $k > -2$ and less responsive when $k < -2$ with forecast integration; see Proposition 1(ii). In either case, the platform adjusts the effective freight rate in the opposite direction from the wholesale price so as to offset its effect on the retail quantity. For example, when the spot rate forecast leads to a lower wholesale price (i.e., when posterior mean increases for $k > -2$ or decreases for $k < -2$), retail quantity increases to allow for a higher platform rate while maintaining shipping volume. As we will show, this *platform rate counter-response* has profound implications for supply chain profits and forecast integration adoption.

Proposition 1(iii) characterizes how forecast integration affects the equilibrium retail quantity. Although this depends on both responsive wholesale pricing and the platform rate counter-response, the former dominates, so the retail quantity is less responsive to the posterior mean of spot rate when $k > -2$ and more responsive when $k < -2$. This immediately yields the following results.

COROLLARY 1. *Forecast integration leads to lower variability of the equilibrium order quantity (i.e.,* $\mathtt{Var}\left[q^{\mathtt{I}}\right] < \mathtt{Var}\left[q^{\mathtt{N}}\right]$*) when* $k > -2$*, and higher variability (i.e.,* $\mathtt{Var}\left[q^{\mathtt{I}}\right] > \mathtt{Var}\left[q^{\mathtt{N}}\right]$*) when* $k < -2$*.*

Next, we examine the impact of posterior second moment $\mathtt{E}[\epsilon^2 \mid \xi]$ as a proxy of the magnitude of spot rate randomness. As discussed previously, a higher $\mathtt{E}[\epsilon^2 \mid \xi]$ inferred from a larger absolute value of ξ indicates a higher expected shipping cost of platform carriers, i.e., $\delta(S)\kappa(S)$. This leads to wholesale price adjustment and further affects the effective platform rate and the retail quantity, as analyzed below.

PROPOSITION 2. *(i) Wholesale price* $w^{\mathtt{I}}$ *is decreasing in* $\mathtt{E}[\epsilon^2 \mid \xi]$ *when* $k > -2$*, and is increasing in* $\mathtt{E}[\epsilon^2 \mid \xi]$ *when* $k < -2$*.*

(ii) Effective platform rate $r^{\mathtt{I}}\mathtt{E}[\delta(S) \mid \xi]$ *is increasing in* $\mathtt{E}[\epsilon^2 \mid \xi]$*, as in the case without forecast integration, but is more responsive when* $k > -2$ *and less responsive when* $k < -2$*.*

(iii) Order quantity $q^{\mathtt{I}}$ *is decreasing in* $\mathtt{E}[\epsilon^2 \mid \xi]$*, as in the case without forecast integration, but is less responsive when* $k > -2$ *and more responsive when* $k < -2$*.*

A higher $\mathtt{E}[\epsilon^2 \mid \xi]$ indicates a higher expected platform shipping cost and leads the platform to raise the effective freight rate and the retailer to lower the order quantity with or without forecast integration. Forecast integration alters the responsiveness of these decisions by allowing the wholesale price to adjust to the spot rate forecast. Specifically, when $k > -2$, forecast integration leads the manufacturer to make the wholesale price less responsive to the posterior mean to extract greater surplus from the retailer (see the discussion of Proposition 1). In this case, a higher posterior second moment raises the platform's effective rate and depresses the retail quantity. To mitigate this order quantity reduction, the manufacturer lowers the wholesale price, so platform effective rate increases more and retail quantity decreases less in $\mathtt{E}[\epsilon^2 \mid \xi]$ with than without forecast integration.

When $k < -2$, by contrast, forecast integration induces a more responsive (to posterior mean) wholesale price to amplify retail quantity variability and lower the expected production cost due to strong production economy. A higher $\mathtt{E}[\epsilon^2 \mid \xi]$ strengthens this benefit as it indicates a larger magnitude of spot rate deviation from the mean. This leads the manufacturer to raise the wholesale price, which makes the platform's effective rate increase less and the retailer's order quantity decrease more in $\mathtt{E}[\epsilon^2 \mid \xi]$ with than without forecast integration.

Remark 1. Although Propositions 1 and 2 present similar comparative statics, posterior mean and second moment affect equilibrium decisions differently because the spot rate forecast updates them differently by (9). For example, a positive and a negative ξ in the same magnitude induce opposite adjustments in the platform's effective freight rate and the retailer's order quantity through the posterior mean, but induce the same adjustment through the posterior second moment. This difference arises because the posterior mean affects decisions by shifting the updated expected level of the spot rate, whereas the posterior second moment affects decisions by changing the updated magnitude of spot rate randomness.

Our results above offer several novel insights into how supply chains and digital freight platforms should design decision rules under forecast integration. First, wholesale pricing, retail quantity, and platform freight rate decisions should depend not only on the posterior mean but also on the posterior second moment, because the latter provides updated information about the freight platform's expected shipping cost. Second, the platform should set the freight rate rule to counteract the effect of responsive wholesale pricing on the supply chain. In particular, forecast integration can make the platform rate more or less responsive to the posterior mean, depending on the degree of production (dis)economy. Third, forecast integration can make the retailer's order quantity either more or less responsive. These results complement Ha et al. (2011), which shows that sharing demand information with the manufacturer makes the retail quantity less responsive and that supply chain decisions depend on the posterior mean (but not second moment) of market size.

3.2. Value of Forecast Integration

We substitute the equilibrium decisions presented in Section 3.1 into profit expressions of the manufacturer, the retailer, the platform with and without forecast integration, and obtain

$$\Pi_M^{\mathtt{N}} = \frac{(k+4)(u-c)^2}{2(k+6)^2} - \frac{k(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2}{32}\eta, \tag{13}$$

$$\Pi_R^{\mathtt{N}} = \frac{(u-c)^2}{(k+6)^2} + \frac{(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2}{16}\eta, \tag{14}$$

$$\Pi_P^{\mathtt{N}} = 2\Pi_R^{\mathtt{N}}, \tag{15}$$

$$\Pi_M^{\mathtt{I}} = \frac{(k+4)(u-c)^2}{2(k+6)^2} + \frac{(k+4)(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2}{2(k+6)^2}\eta, \tag{16}$$

$$\Pi_R^{\mathtt{I}} = \frac{(u-c)^2}{(k+6)^2} + \frac{(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2}{(k+6)^2}\eta, \tag{17}$$

$$\Pi_P^{\mathtt{I}} = 2\Pi_R^{\mathtt{I}}, \tag{18}$$

where $\eta := \mathtt{E}_\xi[(\mathtt{E}_\epsilon[\epsilon \mid \xi])^2] = \mathtt{Var}\big[\mathtt{E}_\epsilon[\epsilon \mid \xi]\big] = \frac{\sigma^4}{\sigma^2+1/\tau}$. We compare equilibrium expected profits of each market participant with vs. without forecast integration to obtain its value, as given by:

$$V_M = \Pi_M^{\mathtt{I}} - \Pi_M^{\mathtt{N}} = \frac{(k+2)(k^2+10k+32)(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2}{32(k+6)^2}\eta, \tag{19}$$

$$V_R = \Pi_R^{\mathtt{I}} - \Pi_R^{\mathtt{N}} = -\frac{(k+2)(k+10)(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2}{16(k+6)^2}\eta, \tag{20}$$

$$V_P = \Pi_P^{\mathtt{I}} - \Pi_P^{\mathtt{N}} = 2V_R. \tag{21}$$

Based on these expressions, we analyze the profit implications of forecast integration as follows.

PROPOSITION 3. *(i) When $k > -2$, forecast integration benefits the manufacturer, hurts the retailer and the platform, and benefits the supply chain, i.e., $V_M > 0$, $V_R < 0$, $V_P < 0$, $V_M + V_R > 0$.*

(ii) When $k < -2$, forecast integration hurts the manufacturer, benefits the retailer, the platform, and the supply chain, i.e., $V_M < 0$, $V_R > 0$, $V_P > 0$, and $V_M + V_R > 0$.

When production exhibits diseconomy or weak economy (i.e., $k > -2$), forecast integration benefits the manufacturer but hurts the retailer. This is due to responsive wholesale pricing that dampens order quantity variability and strengthens double marginalization (see Ha et al. 2011, and references therein). However, in contrast to the literature where demand information sharing benefits supply chain only under strong production diseconomy, forecast integration benefits the supply chain for the full range of $k > -2$. This is because *responsive wholesale pricing lowers the retailer's expected shipping cost* by inducing platform rate counter-response. Specifically, a lower (resp. higher) spot rate forecast induces a higher (resp. lower) wholesale price, which leads the platform to reduce (resp. raise) the freight rate. Because the retailer orders and ships more at a lower spot rate forecast, the platform rate counter-response reduces the expected total shipping cost. Thus, forecast integration benefits the supply chain but hurts the platform.

When production exhibits strong economy (i.e., $k < -2$), forecast integration benefits the retailer but hurts the manufacturer. This is because responsive wholesale pricing amplifies variability of the retail quantity which is thus more responsive to the spot market; see Corollary 1. The manufacturer, however, is worse off despite that increased retail/order quantity variability reduces the expected production cost. The manufacturer cannot reap the full benefits from this due to the platform rate counter-response. For example, when the spot rate forecast is lower, the manufacturer reduces the wholesale price to increase the order quantity. This, however, is counter-balanced by the platform raising the effective freight rate. As a result, forecast integration makes the manufacturer worse off and the platform better off. Interestingly, the supply chain is better off because the benefit of responsive wholesale pricing in reducing the expected production cost and mitigating double marginalization dominates the loss from platform rate counter-response.

Our results above contribute to the literature on information sharing in supply chains in several aspects. First, we demonstrate the value of forecast integration for supply chains. Perhaps surprisingly, forecast integration always benefits the supply chain for any production (dis)economy level. This contrasts to the literature which shows that sharing demand information upstream benefits the supply chain only under strong production diseconomy. Second, we identify novel mechanisms underlying the value of forecast integration and show that the expected freight cost and platform rate counter-response play critical roles. Third, although forecast integration always benefits the supply chain, it may increase or decrease profits of the manufacturer, the retailer, and the platform, depending on the level of production (dis)economy.

3.3. Forecast Integration Adoption

Now, we synthesize results above to characterize the equilibrium adoption of forecast integration, access price P^*, transfer payment T^*, and net profits of all market participants as presented below.

PROPOSITION 4. *(i) Forecast integration is adopted in equilibrium iff $k > 2(2\sqrt{2}-1)$ or $k < -2$.*

(ii) Equilibrium transfer payment $T^* > 0$ when $k > 2(2\sqrt{2}-1)$, and $T^* < 0$ when $k < -2$.

(iii) In equilibrium, the manufacturer and the retailer obtain net profits $\Pi_M^{\mathtt{N}}$ and $\Pi_R^{\mathtt{N}}$ for any k. The platform obtains net profit $\Pi_P^{\mathtt{I}} + V_R + V_M$ when $k > 2(2\sqrt{2}-1)$ or $k < -2$, and $\Pi_P^{\mathtt{N}}$ otherwise.

Although forecast integration always benefits the supply chain, Proposition 4(i) shows that it is adopted in equilibrium only under sufficiently strong production diseconomy or economy. When $k < -2$, forecast integration benefits the supply chain and the platform, thus it is adopted. Otherwise, forecast integration benefits the supply chain but hurts the platform, and the equilibrium adoption depends on its total value $V_P + V_R + V_M$; see Section 2. When production diseconomy is sufficiently strong (i.e., $k > 2(2\sqrt{2}-1)$), the benefit of forecast integration to the manufacturer in using responsive wholesale pricing to reduce the expected production cost outweighs the profit loss of the retailer and the platform, thus forecast integration is adopted.

Proposition 4(ii) characterizes the equilibrium transfer payment and shows that the direction depends on production (dis)economy as it alters the value of forecast integration for the manufacturer and the retailer. When production exhibits strong diseconomy, forecast integration benefits the manufacturer but hurts the retailer, so to incentivize retailer adoption of forecast integration, the manufacturer should make transfer payment. The opposite is true under strong production economy. As noted in Section 2, either direction is feasible as forecast integration requires the retailer to share the spot rate forecast and the manufacturer to automate the wholesale price contingent on the forecast.

Proposition 4(iii) presents the impact of forecast integration on net profits of all market participants. In equilibrium, the platform uses the access price P^* to extract the full benefit of forecast integration for the supply chain. As a result, the net profits of the manufacturer and the retailer are the same with vs. without forecast integration, whereas the platform benefits $V_M + V_R + V_P > 0$ whenever forecast integration is adopted. This further indicates that, mitigating production diseconomy through, e.g., more efficient technology or learning-by-doing, can have an unexpected impact on the platform's net profit due to a regime shift in forecast integration adoption.

PROPOSITION 5. *In equilibrium, the platform's net profit decreases in k iff $k > 2(2\sqrt{2}-1)$ and* $(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2\eta > \frac{(u-c)^2}{2(\sqrt{2}+1)}$.

Although mitigating production diseconomy (i.e., a lower k) always increases the manufacturer's and the retailer's equilibrium net profits $\Pi_M^{\mathtt{N}}$ and $\Pi_R^{\mathtt{N}}$ in (13)-(14), it first increases and then decreases the platform's net profit when $(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2\eta > \frac{(u-c)^2}{2(\sqrt{2}+1)}$; see Figure 3. This is probably counter to intuition, given that a lower k reduces the total production cost at any retail quantity. Indeed, without forecast integration, a lower k always improves the platform's net profit $\Pi_P^{\mathtt{N}} = 2\Pi_R^{\mathtt{N}}$ by (14)-(15). With forecast integration, however, a lower k can decrease the platform's net profit $\Pi_P^{\mathtt{I}} + V_R + V_M$ when $k > 2(2\sqrt{2}-1)$. In this case, the manufacturer uses responsive wholesale pricing to reduce order quantity variability, which reduces the production and shipping costs. When $(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2\eta > \frac{(u-c)^2}{2(\sqrt{2}+1)}$ and $k > 2(2\sqrt{2}-1)$, a lower k reduces such benefits of responsive wholesale pricing more than it saves the production cost. As a result, the platform's net profit decreases.

3.4. Impact of Freight Rejection Mitigation

In this subsection, we examine the profit implications of freight rejection mitigation strategies and show that forecast integration plays an important role. Freight rejection becomes more likely when the spot rate increases, but this can be mitigated by cultivating shipper-carrier relationships and

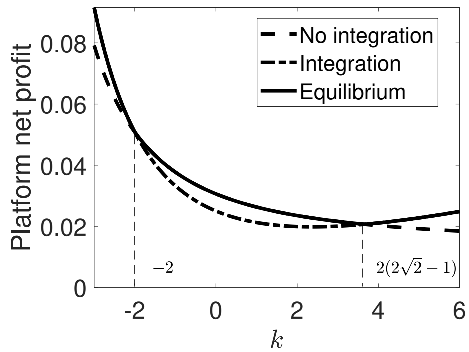


Figure 3 **Impact of production (dis)economy** k **on the platform's equilibrium net profit** ($a = 2, c = 0, s = 2, \alpha = 0.3, \beta = 0.2, v = 0, \rho = 0.8, r_C = 1, \tau = 1000, \sigma = 0.5$)

improving contract explicitness (Scott et al. 2017, 2020). Motivated by these practices, we consider freight rejection mitigation strategies as reducing the sensitivity of freight rejection probability to the spot rate captured by β. We start by analyzing the profit implications of a lower β with and without forecast integration.

LEMMA 1. *For each* $i \in \{\mathtt{N}, \mathtt{I}\}$*, as* β *decreases,*
(i) Π_R^i *decreases if* $\beta > \hat{\beta}_R^i$ *and increases if* $\beta < \hat{\beta}_R^i$*.*
(ii) $\Pi_M^i + \Pi_R^i$ *decreases if* $\beta > \hat{\beta}^i$ *and increases if* $\beta < \hat{\beta}^i$*.*

With or without forecast integration, a lower β causes both retailer and supply chain profits to first decrease and then increase. The increasing part is intuitive, as a lower β reduces the freight rejection probability $\delta(S)$ for any spot rate S, thereby reducing the expected shipping cost. More interestingly, when β is larger, a lower β reduces retailer and supply chain profits despite lowering the expected shipping cost. This is because a lower β weakens the responsiveness of order quantity to the spot market condition. Specifically, at a lower β, the retailer ships through the platform at a lower probability. Since the platform rate is affected by the *a priori* uncertain spot rate, the retailer's order quantity becomes less responsive to the spot rate forecast. This reduces the responsiveness of the supply chain to the spot market, which reduces retailer and supply chain profits.

Building on these results, we next study the role of forecast integration adoption.

PROPOSITION 6. *(i) A lower* β *reduces retailer profit for a larger range, i.e.,* $\beta_R^{\mathtt{I}} < \beta_R^{\mathtt{N}}$*, if* $k > -2$*, and for a smaller range, i.e.,* $\beta_R^{\mathtt{I}} > \beta_R^{\mathtt{N}}$*, if* $k < -2$*.*
(ii) A lower β *reduces supply chain profit for a larger range, i.e.,* $\beta^{\mathtt{I}} < \beta^{\mathtt{N}}$ *for all* k*.*

Proposition 6 shows that forecast integration causes freight rejection mitigation to reduce supply chain profit for a larger range, and to reduce retailer profit for a larger range if $k > -2$ but for a smaller range if $k < -2$. The key reason is that freight rejection mitigation weakens responsive wholesale pricing: a lower β reduces the retailer's exposure to the *a priori* uncertain platform rate, which in turn makes the wholesale price less responsive to the spot rate forecast. When $k < -2$, responsive wholesale pricing mitigates double marginalization and reduces expected production cost. Therefore, by weakening responsive wholesale pricing, freight rejection mitigation undermines these benefits of forecast integration and reduces retailer and supply chain profits for a larger range.

When $k > -2$, however, freight rejection mitigation decreases retailer profit for a smaller range but decreases supply chain profit for a larger range. The former part is expected as freight rejection mitigation weakens responsive wholesale pricing which intensifies double marginalization when $k > -2$. This would presumably suggest a larger range for freight rejection mitigation to increase supply chain profit. However, we find the opposite to be true. This is because freight rejection mitigation also weakens the responsiveness of the order quantity to the spot market condition, and disproportionately more under forecast integration as freight rejection mitigation weakens responsive wholesale pricing. As such, a lower β makes the supply chain even less responsive to the spot market under forecast integration, so supply chain profit decreases for a larger range.

Our results in this subsection offer novel insights into truckload transportation. Existing studies largely treat freight rejection mitigation as inherently beneficial for shippers and explore effective mitigation strategies. In contrast, we show that freight rejection mitigation can backfire considering supply chain interactions. By reducing the supply chain's exposure to spot market conditions, it can lower the responsiveness of wholesale pricing and order quantity, thereby reducing shipper/retailer and supply chain profits. Moreover, forecast integration moderates these effects in a nontrivial manner. Depending on the degree of production (dis)economy, forecast integration can either increase or decrease the attractiveness of freight rejection mitigation for the retailer. Overall, our results suggest that retailers should exercise caution in pursuing freight rejection mitigation and forecast integration, because their dual role as both retailer and shipper can create subtle trade-offs across shipping, wholesale pricing, and order/shipping quantity decisions.

4. Additional Considerations

In this section, we incorporate several additional considerations, i.e., extending our modeling of forecast integration adoption to a generalized Nash bargaining framework in Section 4.1, explicitly modeling the impact of contract carrier's freight rate on freight rejection in Section 4.2, and calibrating our model to real-world data in Section 4.3. We will demonstrate the robustness of main insights in Section 3 and derive additional insights.

4.1. Generalized Nash Bargaining

In the main model, the manufacturer sets transfer payment T to the retailer to induce forecast adoption, and then the retailer decides whether to adopt (see Figure 2). Here, we generalize this to allow the manufacturer and the retailer to bargain over the transfer payment in a Nash bargaining framework; see Shi et al. (2021) and Chen et al. (2023) for similar formulations. Specifically, for a given access price P, the transfer payment to induce forecast integration adoption is determined by solving the following problem:

$$\max_{T} \left(V_R - P + T\right)^{\theta} \left(V_M - T\right)^{1-\theta}, \text{ such that } V_R - P + T \geq 0 \text{ and } V_M - T \geq 0, \tag{22}$$

where $\theta \in [0,1]$ denotes the retailer's bargaining power and $1-\theta$ is the manufacturer's bargaining power; we normalize their disagreement payoffs to zero. Solving this problem yields the transfer payment to induce adoption as $T = (1-\theta)(P - V_R) - \theta V_M$. Under this transfer payment, the manufacturer obtains net profit $\Pi_M^{\mathtt{N}} + (1-\theta)(V_R + V_M - P)$, the retailer obtains net profit $\Pi_R^{\mathtt{N}} + \theta(V_R + V_M - P)$, and the platform obtains net profit $\Pi_P^{\mathtt{I}} + P$. In contrast, if forecast integration is not adopted, the manufacturer, retailer, and platform obtain net profits $\Pi_M^{\mathtt{N}}$, $\Pi_R^{\mathtt{N}}$, and $\Pi_P^{\mathtt{N}}$, respectively. Note that when $\theta = 0$, the retailer has no bargaining power, and the transfer payment reduces to the one in the main model (see Section 2). As θ increases, the retailer captures a larger share of the surplus from forecast integration, while the manufacturer captures a smaller share.

We derive the equilibrium outcome and find that the equilibrium adoption of forecast integration, the direction of transfer payment T^*, and each market participant's equilibrium profit are identical to those in the main model presented in Proposition 4; see Section EC.2.1 in the E-Companion for the detailed analysis. These results demonstrate robustness of our results in a more general setting where the adoption of forecast integration is determined by Nash bargaining between the manufacturer and the retailer. This bargaining affects how they share gains from forecast integration but does not affect its equilibrium adoption as it depends on the total value for the supply chain.

4.2. Impact of Contract Carrier's Freight Rate

In the main model, we treat the contract carrier's freight rate r_C as fixed because, in truckload markets, contract rates are typically determined before the selling season through annual procurement auctions and then remain fixed for an extended period (e.g., one year). This allows us to focus on the role of spot market conditions in driving freight rejection. In practice, however, the long-term contract rate can also affect freight rejection incentives. Intuitively, a higher r_C makes it more attractive for the contract carrier to accept the tendered shipment rather than reject it and seek spot market opportunities. Scott et al. (2017) empirically observe that freight rejection becomes more likely as spot-to-contract rate ratio, i.e., S/r_C, increases.

In this subsection, we incorporate this effect and examine the impact of contract carrier's freight rate. Specifically, we set $\beta = \lambda/r_C$ so the freight rejection probability $\delta(S) = \alpha + \lambda(S/r_C)$ is linearly increasing in the spot-to-contract rate ratio S/r_C with slope $\lambda > 0$. All results from the main model continue to hold for any given r_C, thus we focus on the impact of r_C on the equilibrium outcomes.

PROPOSITION 7. *(i) Retailer's equilibrium net profit first increases and then decreases in r_C.*
(ii) Platform's equilibrium net profit first increases and then decreases in r_C, and the range for the net profit to increase is smaller when forecast integration is adopted.

A higher contract rate r_C increases the retailer's freight cost through the contract carrier, whereas it also lowers the freight rejection probability and thus reduces the expected use of the more expensive platform shipping. Therefore, the retailer's equilibrium net profit, which is equal to $\Pi_R^{\mathtt{N}}$ with or without forecast integration, first increases and then decreases in r_C.

The platform's equilibrium net profit also first increases and then decreases in r_C. When r_C is low, a higher contract rate reduces freight rejection and improves overall supply chain efficiency, which increases shipping activity and benefits the platform. When r_C is high, however, the direct increase in the retailer's shipping cost dominates, reducing order and shipping quantity and thereby lowering the platform's net profit. More interestingly, the range for a higher r_C to increase platform profit is smaller with than without forecast integration. The reason is that a higher r_C mitigates freight rejection, which under forecast integration, weakens responsive wholesale pricing and leads the ordering/shipping quantity to be less responsive to spot market conditions (see discussions in Section 3.4). This makes platform less effective to profit from pricing based on the spot rate forecast, thus lowers its revenue from handling shipping.

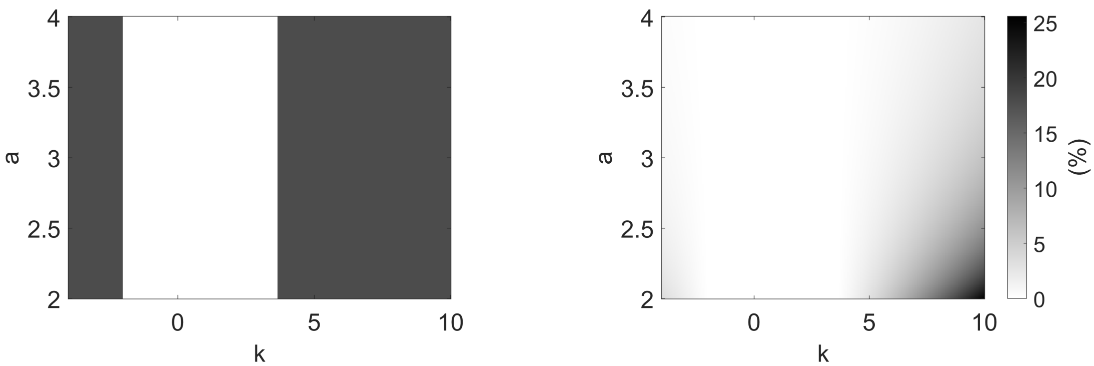
4.3. Numerical Calibration

In this section, we calibrate our main model described in Section 2 to real-world data, verify robustness of main results, and quantify profit gains from forecast integration.

We calibrate our model as follows. First, we use freight rejection probability $\delta(S) = e^{1.864S/r_C - 4.774}/(e^{1.864S/r_C - 4.774} + 1)$ estimated by Scott et al. (2017) using transaction data from a large U.S. shipper.[4] Second, we estimate the platform's freight cost $\kappa(S)$ using proprietary transaction data from a leading digital freight platform in China. The dataset contains daily spot freight rates and payments to platform carriers from May to November 2023. To identify an appropriate functional form for $\kappa(S)$, we estimate three specifications: a proportional model, a linear model with an intercept, and a quadratic model. We use proportional specification $\kappa(S) = \rho S$ as it provides the

[4] Specifically, coefficient 1.864 is taken from the "spot premium" estimate in Table 2 of Scott et al. (2017). We compute $-4.774 = -4.83 + 0.0904 \times 0.287 + 0.0128 \times 2.375$ based on their regression model in (3) and Tables 1 and 2.

best fit with an estimated $\rho = 0.72$ ($p < 0.001$) and a high $R^2 = 0.97$. Third, we normalize the contracted carrier's rate to $r_C = 1$ and use average spot rate $s = 1.489$ according to Scott et al. (2017). As in Ha et al. (2011), we normalize $c = 0$. It is without loss of generality as c enters equilibrium outcomes only through a constant part and thus does not affect incentives for forecast integration. Fourth, we consider realistic ranges for other parameters as they are market- or product-specific: $k \in [-4, 10]$, $a \in [2, 4]$, $\sigma \in [0.2, 0.8]$, and $\mathtt{E}[\mathtt{Var}[\xi \mid \epsilon]] = 0.04\sigma$ which implies $\tau \in [31.25, 125]$.



(a) Equilibrium adoption (gray region indicates adoption)

(b) Value of forecast integration $\frac{V_M + V_R + V_P}{\Pi^{\mathrm{N}}_M + \Pi^{\mathrm{N}}_R + \Pi^{\mathrm{N}}_P}$

Figure 4 **Equilibrium adoption and value of forecast integration** ($r_c = 1$, $c = 0$, $s = 1.489$, $\sigma = 0.5, \tau = 50$, $\delta(S) = e^{1.864S - 4.774}/(e^{1.864S-4.774} + 1)$, $\kappa(S) = 0.72S$)

We have verified that all analytical results in Section 3 hold qualitatively under calibrated data and realistic functions of $\delta(S)$ and $\kappa(S)$. In addition, we quantify the value of forecast integration when it is adopted. As illustrated in Figure 4(b), forecast integration increases system profit by 2.69% on average and as much as 25.56%. Qualitatively, forecast integration generates the largest percentage value to the system under strong production diseconomy and low market size. This is because stronger production diseconomy amplifies the benefit of forecast integration in mitigating responsive wholesale pricing and lowering the expected production cost, while a lower market size lowers system profits without forecast integration so its benefit is more prominent.

5. Competing Supply Chains

In this section, we consider forecast integration in two supply chains indexed by $i \in \{1, 2\}$ under Cournot competition as in Ha et al. (2011, 2017). Thus, the market-clearing price p_i in supply chain i is given by $p_i = a - q_i - \gamma q_j$, where $\gamma \in (0, 1)$ represents the intensity of competition, and q_i and q_j denote the retail quantities of retailers in supply chains i and j, respectively. The supply chains are symmetric and have same production and freight cost structures. Moreover, since the two supply chains compete in the same market, they share the same spot rate S forecasted by the platform at $\hat{S}$; see Section 2.

The sequence of events in the no forecast integration case is identical to the main model, with forecast integration, the platform posts an access price P for both retailers, and then each manufacturer i determines the transfer payment T_i to retailer i, where we use supply chain index $i \in \{1,2\}$ to refer to the manufacturer and the retailer in that supply chain. Next, the two retailers simultaneously and independently decide whether to implement forecast integration. We use superscript $\Upsilon_i \in \{\mathtt{N},\mathtt{I}\}$ to denote the case of integration (i.e., $\Upsilon_i = \mathtt{I}$) or no integration (i.e., $\Upsilon_i = \mathtt{N}$ in supply chain i). Next, the game proceeds as in the main model; see Figure 2.

We make the following assumptions. First, the state of forecast integration adoption in each supply chain is public information; see similar assumptions in Ha et al. (2011), Shang et al. (2016), Ha et al. (2017). In practice, this arises because related activities of forecast integration (such as system setup for API access) can be observed or obtained from third parties (e.g., consultants). Second, we assume that the platform can charge different freight rates r_1 and r_2 to the two retailers, reflecting the common practice among digital freight platforms of customizing freight rates independently with each client (Cargofive 2025). Furthermore, the platform is prohibited from disclosing r_i to retailer j due to privacy restrictions (Coughlan and Wernerfelt 1989, Liu et al. 2021).

Note that the wholesale price w_i and retail quantity q_i within supply chain i are observable only to that supply chain and remain private from the rival supply chain j. Furthermore, when setting the freight rate r_i for retailer i, the platform does not observe the retail quantity chosen by supply chain j. Following the literature (e.g., Ha et al. (2011), Shang et al. (2016)), we assume that retailer i, manufacturer i, and the platform share a common belief $q_j(\cdot)$ about the retail quantity of the rival supply chain j. Based on this common belief, we conduct analysis as in the main model to derive the equilibrium retail quantity for supply chain i under each $\Upsilon_i \in \{\mathtt{N},\mathtt{I}\}$, denoted by $q_i^{\Upsilon_i}(q_j(\cdot))$. Similarly, we obtain the equilibrium retail quantity of supply chain j, denoted by $q_j^{\Upsilon_j}(q_i(\cdot))$, where $q_i(\cdot)$ is the corresponding common belief held by supply chain j regarding the retail quantity of supply chain i. We then characterize the Perfect Bayesian equilibrium $(q_i^{\Upsilon_i,\Upsilon_j}(\cdot), q_j^{\Upsilon_j,\Upsilon_i}(\cdot))$, which requires decisions and beliefs to be mutually consistent, i.e., $q_i^{\Upsilon_i,\Upsilon_j}(\cdot) = q_i^{\Upsilon_i}\big(q_j^{\Upsilon_j,\Upsilon_i}(\cdot)\big)$ and $q_j^{\Upsilon_j,\Upsilon_i}(\cdot) = q_j^{\Upsilon_j}\big(q_i^{\Upsilon_i,\Upsilon_j}(\cdot)\big)$.

Given the equilibrium retail quantities, we derive the expected profits of retailer i and manufacturer i, denoted by $\Pi_{R_i}^{\Upsilon_i,\Upsilon_j}$ and $\Pi_{M_i}^{\Upsilon_i,\Upsilon_j}$, respectively. Also let $\Pi_{P_i}^{\Upsilon_i,\Upsilon_j}$ denote the platform's expected profit from serving retailer i. We further define $V_{R_i}^{\Upsilon_j} = \Pi_{R_i}^{\mathtt{I},\Upsilon_j} - \Pi_{R_i}^{\mathtt{N},\Upsilon_j}$ and $V_{M_i}^{\Upsilon_j} = \Pi_{M_i}^{\mathtt{I},\Upsilon_j} - \Pi_{M_i}^{\mathtt{N},\Upsilon_j}$ as the gross values of adopting forecast integration for retailer i and manufacturer i, respectively. Given supply chain j's forecast arrangement, supply chain i adopts forecast integration iff $V_{R_i}^{\Upsilon_j} + V_{M_i}^{\Upsilon_j} \geq P$; otherwise, it does not. Based on this decision rule, we model the adoption of forecast integration across competing supply chains as a simultaneous-move Nash game, in which each supply chain selects a strategy from the action set $\{\mathtt{N},\mathtt{I}\}$. When multiple equilibria arise, we follow the literature (e.g., Shang et al. (2016)) and apply Pareto optimality as a refinement criterion.

5.1. Equilibrium Outcomes

We now derive explicit expressions for the equilibrium retail quantities and profits, and use these results to characterize the equilibrium adoption of forecast integration in the competing supply chains setting. Define $q^{bc} := \frac{u-c}{\gamma+k+6}$, $\Pi_R^{bc} := \frac{(u-c)^2}{(\gamma+k+6)^2}$, $\Pi_M^{bc} := \frac{(k+4)(u-c)^2}{2(\gamma+k+6)^2}$, and $\Pi_P^{bc} := 2\Pi_R^{bc}$. We present equilibrium outcomes and value of forecast integration in the proposition below, where expressions for ϕ, φ, and h parameters are relegated to Table EC.1 in the E-Companion.

Proposition 8. *For each supply chain $i \in \{1,2\}$,*

(i) the equilibrium retail quantity is uniquely given by: $q_i^{\Upsilon_i,\Upsilon_j} = q^{bc} + \phi_{i0}^{\Upsilon_i,\Upsilon_j}\sigma^2 + \phi_{i1}^{\Upsilon_i,\Upsilon_j}\mathtt{E}[\epsilon \mid \xi] + \phi_{i2}^{\Upsilon_i,\Upsilon_j}\mathtt{E}[\epsilon^2 \mid \xi]$, and the corresponding expected profits are:

$$\Pi_{R_i}^{\Upsilon_i,\Upsilon_j} = \Pi_R^{bc} + \varphi_R^{\Upsilon_i,\Upsilon_j}\big(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s)\big)^2\eta,$$
$$\Pi_{M_i}^{\Upsilon_i,\Upsilon_j} = \Pi_M^{bc} + \varphi_M^{\Upsilon_i,\Upsilon_j}\big(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s)\big)^2\eta,$$
$$\Pi_{P_i}^{\Upsilon_i,\Upsilon_j} = \Pi_P^{bc} + \varphi_P^{\Upsilon_i,\Upsilon_j}\big(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s)\big)^2\eta.$$

(ii) When $k > -2$ (resp., $k < -2$), $V_{R_i}^{\Upsilon_j} < 0$ and $V_{M_i}^{\Upsilon_j} > 0$ (resp., $V_{R_i}^{\Upsilon_j} > 0$ and $V_{M_i}^{\Upsilon_j} < 0$).

(iii) For any k, $V_{R_i}^{\Upsilon_j} + V_{M_i}^{\Upsilon_j} = h^{\Upsilon_j}(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s))^2\eta > 0$, where $h^{\mathtt{I}} > h^{\mathtt{N}} > 0$ if $k > -2$, and $h^{\mathtt{N}} > h^{\mathtt{I}} > 0$ if $k < -2$.

Proposition 8(i) shows that the equilibrium retail quantity of each supply chain i is a linear function of $\mathtt{E}[\epsilon \mid \xi]$ and $\mathtt{E}[\epsilon^2 \mid \xi]$, where $\phi_{i1}^{\Upsilon_i,\Upsilon_j}$ and $\phi_{i2}^{\Upsilon_i,\Upsilon_j}$ are the response coefficients of $q_i^{\Upsilon_i,\Upsilon_j}$ with respect to the signal. Using the equilibrium quantity, we find that impact of forecast integration by the focal supply chain i on the variability of its own retail quantity is identical to that in Proposition 2(iii). By contrast, forecast integration by the rival supply chain j has the opposite effect on the focal supply chain i's retail quantity variability: it increases variability (i.e., $\mathtt{Var}\big[q_i^{\Upsilon_i,\mathtt{I}}\big] \geq \mathtt{Var}\big[q_i^{\Upsilon_i,\mathtt{N}}\big]$) when $k > -2$, and reduces it (i.e., $\mathtt{Var}\big[q_i^{\Upsilon_i,\mathtt{I}}\big] \leq \mathtt{Var}\big[q_i^{\Upsilon_i,\mathtt{N}}\big]$) when $k < -2$, for any forecast arrangement $\Upsilon_i \in \{\mathtt{N},\mathtt{I}\}$ of the focal supply chain i. Moreover, $\mathtt{Var}\big[q_i^{\Upsilon_i,\Upsilon_j}\big]$ decreases as γ increases.

Proposition 8(i) also characterizes every player's expected profit. For example, each retailer i's expected profit, $\Pi_{R_i}^{\Upsilon_i,\Upsilon_j}$, comprises two components: a baseline term Π_R^{bc} and a signal-driven term $\varphi_R^{\Upsilon_i,\Upsilon_j}\big(\beta(v+\rho s - r_C) + \rho(\alpha+\beta s)\big)^2\eta$. The baseline Π_R^{bc} reflects prior knowledge about freight rejection, while the signal-driven term depends on posterior information and increases with signal informativeness τ (since $\eta = \frac{\sigma^4}{\sigma^2+1/\tau}$ is increasing in τ). Notably, Π_R^{bc} decreases with competition intensity γ: as γ rises, the average market demand facing retailer i declines. The signal-driven term likewise decreases with γ (or equivalently, $\varphi_R^{\Upsilon_i,\Upsilon_j}$ is decreasing in γ) owing to the dampening effect of stronger competition on the variability of the equilibrium retail quantity.

Based on the expected profits, we calculate the gross values of forecast integration for retailer i and manufacturer i relative to the no-integration case, as shown in Proposition 8(ii). These results are consistent with results in the main model. Proposition 8(iii) also shows that the gross value of forecast integration to supply chain i is always positive. Moreover, the relationship $h^{\mathtt{I}} > h^{\mathtt{N}}$ if $k > -2$ (resp., $h^{\mathtt{N}} > h^{\mathtt{I}}$ if $k < -2$) indicates that this gross value is higher (resp., lower) when the rival supply chain j also adopts forecast integration than when it does not. This result follows naturally from our earlier observation that the rival's forecast integration increases (resp., decreases) the variability of the focal supply chain i's retail quantity when $k > -2$ (resp., $k < -2$), thereby amplifying (resp., dampening) the benefit of integration for supply chain i.

Building on Proposition 8, we are ready to show the equilibrium adoption of forecast integration in competing supply chains; we relegate expressions of k-threshold to Appendix EC.3.3 for brevity.

Proposition 9. *There exists threshold $\bar{k} > 0$ which decreases in γ such that both supply chains adopt forecast integration if $k > \bar{k}$ or $k < -2$; otherwise, neither supply chain adopts. The impact of β on each retailer's and supply chain's profits is the same as in Lemma 1 and Proposition 6.*

Proposition 9 shows that our results regarding the equilibrium adoption of forecast integration and the impact of freight rejection mitigation from Section 3 continue to hold qualitatively with supply chain competition. More interestingly, increased competition intensity as represented by a higher γ expands the range of k in which forecast integration is adopted in equilibrium, i.e., $\bar{k}$ decreases in γ. This is because intensified competition amplifies the effect of forecast integration in reducing order quantity variability, which lowers the expected shipping cost (see the discussion of Proposition 3). For example, a lower posterior mean of the spot rate leads each retailer to order more, but less so under forecast integration due to responsive wholesale pricing. This effect is stronger under more intense competition: the competing retailer also increases her order quantity, which reduces the focal retailer's effective market size and further weakens her incentive to order more in response to the lower posterior mean of the spot rate.

6. Concluding Remarks

This paper examines the supply chain implications of forecast integration by digital freight platforms under freight rejection. Motivated by the dual roles of digital freight platforms as backup freight and logistics analytics providers, we develop a game-theoretic model of a manufacturer, a retailer, and a digital freight platform. Our analysis shows that forecast integration gives rise to a nontrivial strategic interaction between the manufacturer's responsive wholesale pricing and the platform's freight rate decision. In particular, the manufacturer's forecast-contingent wholesale price induces a countervailing response from the platform, which adjusts its freight rate to offset the effect of wholesale pricing on the retailer's order quantity. Through this mechanism, forecast integration always benefits the supply chain, although its value to the manufacturer, the retailer, and the platform depends on the degree of production (dis)economy. We further show that forecast integration is adopted in equilibrium only when production exhibits sufficiently strong economy or diseconomy, and that freight rejection mitigation can unintentionally reduce retailer and supply chain profits by weakening supply chain responsiveness to spot market conditions.

Our findings yield several actionable insights for supply chains and digital freight platforms. First, forecast integration reshapes wholesale pricing, order quantity, and platform rate decisions. In particular, firms should design decision rules under forecast integration based not only on the posterior mean of the spot rate but also on its posterior second moment which provides updated information on the expected shipping cost. Second, we caution retailers about combining forecast integration with freight rejection mitigation strategies, such as cultivating long-term shipper–carrier relationships or improving contract explicitness, because these levers can interact in ways that reduce the value of forecast integration. Third, we suggest that digital freight platforms target forecast integration toward supply chains with pronounced production economy or diseconomy, where the value created by integration is greatest, and recognize that the profitability of forecast integration depends on production characteristics in supply chains.

To derive sharp analytical insights into forecast integration, we adopt several simplifying assumptions, which naturally open avenues for future research. For example, we focus on a realistic setting in which the retailer is responsible for shipping the product. One could consider alternative settings in which the manufacturer is responsible for shipping, or more generally, the manufacturer and retailer jointly determine the allocation of shipping responsibility. In addition, one could extend our analysis of competing supply chains to allow for asymmetric freight rejection probabilities and examine how such heterogeneity affects the value and adoption of forecast integration. Finally, building on our model, one could incorporate a dedicated bidding or procurement model to endogenize the long-term contract rate and study its interaction with forecast integration adoption decisions and short-term wholesale pricing, retailer ordering, and platform freight pricing decisions.

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E-Companion of "Forecast Integration in Supply Chains under Freight Rejection"

EC.1. Proofs of Results in Section 3

EC.1.1. Derivation of Equilibrium Outcomes. We derive the equilibrium decisions under each forecast arrangement via backward induction.

No (Forecast) Integration. In this case, the platform shares the signal ξ exclusively with the retailer. Given the wholesale price w and the platform's freight rate r, the retailer maximizes her expected profit function (2). 'This yields the optimal order quantity as follows:

$$\tilde{q}(w,r,\xi) = \frac{a - r_C(1 - \mathtt{E}[\delta(S) \mid \xi])}{2} - \frac{w}{2} - \frac{r\mathtt{E}[\delta(S) \mid \xi]}{2}. \tag{EC-1}$$

Given a wholesale price belief $\hat{w}$, the platform maximizes its expected profit function (3). This gives the optimal freight rate:

$$\tilde{r}(\hat{w},\xi) = \frac{a - r_C(1 - \mathtt{E}[\delta(S) \mid \xi]) + \mathtt{E}[\delta(S)\kappa(S) \mid \xi] - \hat{w}}{2\,\mathtt{E}[\delta(S) \mid \xi]}. \tag{EC-2}$$

Simultaneously, the manufacturer has a belief $r(\xi)$ about the freight rate and maximizes his expected profit function (4). To ensure the concavity of $\Pi_M(\cdot)$, or equivalently $\frac{\partial^2 \Pi_M(\cdot)}{\partial w^2} < 0$, we need $k+4>0$, which leads us to assume $k > -4$. The optimal wholesale price is thus:

$$\tilde{w}(r(\xi)) = \frac{2c + (k+2)(a - r_C(1 - \mathtt{E}[\delta(S)]) - \mathtt{E}[r(\cdot)\,\mathtt{E}[\delta(S) \mid \xi]])}{k+4}. \tag{EC-3}$$

By jointly solving Equation (EC-2) and Equation (EC-3), we derive the wholesale price $w^{\mathtt{N}} = \frac{4c+(k+2)u}{k+6}$ and equilibrium freight rate shown in Equation (7). Substituting the equilibrium wholesale price and freight rate into $\tilde{q}(\cdot)$, we obtain the equilibrium retail quantity shown in Equation (8).

Furthermore, substituting all the equilibrium decisions into every player's profit function, we further obtain their expected profits shown in Equations (13) to (15).

Forecast Integration. In this case, the retailer's optimal order quantity and the platform's optimal freight rate remain as in Equations (EC-1) and (EC-2). Moreover, the manufacturer observes the signal ξ, and maximizes his expected profit function (5), which is also concave under $k > -4$. The optimal wholesale price is:

$$\tilde{w}^{\mathtt{I}*}(r(\xi),\xi) = \frac{2c + (k+2)(a - r_C(1 - \mathtt{E}[\delta(S) \mid \xi]) - r(\cdot)\,\mathtt{E}[\delta(S) \mid \xi])}{k+4}. \tag{EC-4}$$

By jointly solving Equations (EC-2) and (EC-4), we derive the equilibrium freight rate and wholesale prices, shown in Equations (10) and (11), and the equilibrium retail quantity, shown in Equation (12). By substituting the equilibrium decision into every player's expected profit function, we obtain their expected profits shown in Equations (16) to (18). □

EC.1.2. Proofs of Proposition 1. From Equation (10), we find that how $w^{\mathtt{I}}$ responds to the posterior mean $\mathtt{E}[\epsilon \mid \xi]$ depends on the sign of $-(k+2)$, which is negative (resp., positive) when $k > -2$ (resp., $k < -2$), $w^{\mathtt{I}}$ is decreasing (resp., increasing) in the posterior mean $\mathtt{E}[\epsilon \mid \xi]$. This proves (i).

For (ii), we observe that how the effective platform rate $r^{\mathtt{I}}\mathtt{E}[\delta(S) \mid \xi]$ responds to the posterior mean $\mathtt{E}[\epsilon \mid \xi]$ depends on the sign of $(4+k)$, which is always positive. Moreover, we consider: $r^{\mathtt{I}}\,\mathtt{E}[\delta(S) \mid \xi] - r^{\mathtt{N}}\,\mathtt{E}[\delta(S) \mid \xi] =$

$\frac{\mathtt{E}[\epsilon|\xi](k+2)(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s)}{2(k+6)}+\frac{\beta(k+2)\rho(\mathtt{E}[\epsilon^2|\xi]-\sigma^2)}{2(k+6)}$, meaning that the effective platform rate is more (resp., less) responsive when $k>-2$ (resp., $k<-2$).

For (iii), from Equation (12), we find that $q^{\mathtt{I}}$ is decreasing in the posterior mean $\mathtt{E}[\epsilon \mid \xi]$, and consider $q^{\mathtt{I}}-q^{\mathtt{N}}=\frac{\mathtt{E}[\epsilon|\xi](k+2)(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))}{4(k+6)}+\frac{\beta(k+2)\rho(\mathtt{E}[\epsilon^2|\xi]-\sigma^2)}{4(k+6)}$, meaning that the equilibrium retail quantity is less (resp., more) responsive when $k>-2$ (resp., $k<-2$). □

EC.1.3. Proof of Corollary 1. From Equations (8) and (12) we have: $\mathtt{Var}\left[q^{\mathtt{N}}\right]=\frac{1}{16}\mathtt{Var}\left[(-\beta\,(v+\rho s-r_C)+\rho\,(\alpha+\beta s))\mathtt{E}[\epsilon\mid\xi]-\beta\rho\,(\mathtt{E}[\epsilon^2\mid\xi])\right]$ and $\mathtt{Var}\left[q^{\mathtt{I}}\right]=\frac{1}{(6+k)^2}\mathtt{Var}\left[(-\beta\,(v+\rho s-r_C)+\rho\,(\alpha+\beta s))\mathtt{E}[\epsilon\mid\xi]-\beta\rho\,(\mathtt{E}[\epsilon^2\mid\xi])\right]$. As such, we have: $\mathtt{Var}\left[q^{\mathtt{I}}\right]/\mathtt{Var}\left[q^{\mathtt{N}}\right]=(\frac{4}{(k+6)})^2$. This implies that forecast integration makes the equilibrium retail quantity less variable (i.e., $\mathtt{Var}\left[q^{\mathtt{I}}\right]<\mathtt{Var}\left[q^{\mathtt{N}}\right]$) when $k>-2$, and more variable (i.e., $\mathtt{Var}\left[q^{\mathtt{I}}\right]>\mathtt{Var}\left[q^{\mathtt{N}}\right]$) when $k<-2$. □

EC.1.4. Proof of Proposition 2. From Equation (10) we observe that how $w^{\mathtt{I}}$ responds to the term $\mathtt{E}[\epsilon^2\mid\xi]$ depends on the sign of $-(k+2)$, which is negative (resp., positive) when $k>-2$ (resp., $k<-2$). This proves (i).

From Equation (11) we find that how the effective platform rate $r^{\mathtt{I}}\mathtt{E}[\delta(S)\mid\xi]$ responds to $\mathtt{E}[\epsilon^2\mid\xi]$ depends on the sign of $(4+k)$, which is always positive. Moreover, we consider: $r^{\mathtt{I}}\,\mathtt{E}[\delta(S)\mid\xi]-r^{\mathtt{N}}\,\mathtt{E}[\delta(S)\mid\xi]=\frac{\mathtt{E}[\epsilon|\xi](k+2)(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s)}{2(k+6)}+\frac{\beta(k+2)\rho(\mathtt{E}[\epsilon^2|\xi]-\sigma^2)}{2(k+6)}$, meaning that the effective platform rate is more (resp., less) responsive when $k>-2$ (resp., $k<-2$). This proves (ii).

From Equation (12), we find that $q^{\mathtt{I}}$ is decreasing in $\mathtt{E}[\epsilon^2\mid\xi]$, and consider $q^{\mathtt{I}}-q^{\mathtt{N}}=\frac{\mathtt{E}[\epsilon|\xi](k+2)(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))}{4(k+6)}+\frac{\beta(k+2)\rho(\mathtt{E}[\epsilon^2|\xi]-\sigma^2)}{4(k+6)}$, meaning that the equilibrium retail quantity is less (resp., more) responsive when $k>-2$ (resp., $k<-2$). This proves (iii). □

EC.1.5. Proof of Proposition 3. Recall that the values of forecast integration for the retailer, the manufacturer, and the platform are given by Equations (19) to (21).

Note that the values of forecast integration to the retailer and platform, i.e., V_R and V_P, depend on the sign of $-(k+2)$, and the value to the manufacturer V_M depends on the sign of $(k+2)$. As such, when $k>-2$, the values for the retailer and the platform are negative, while that for the manufacturer is positive. When $k<-2$, the values of forecast integration for the retailer and the platform become positive, while that for the manufacturer is negative.

In addition, the value of forecast integration for the entire supply chain is given by: $V_R+V_M=\frac{(k+2)^2(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2}{32(k+6)}\eta$, which is nonnegative for all k. □

EC.1.6. Proof of Proposition 4 . As described in Section 2, the supply chain adopts forecast integration if and only if $P\le V_R+V_M$, with a transfer payment $T=P-V_R$. In other words, if the supply chain adopts forecast integration, the platform sets the optimal access price at V_M+V_R and earns a net profit of $V_P+V_M+\Pi_P^{\mathtt{I}}$. If the supply chain does not adopt forecast integration, the platform earns $\Pi_P^{\mathtt{N}}$. Therefore, the platform chooses forecast integration if $V_P+V_M+\Pi_P^{\mathtt{I}}\ge\Pi_P^{\mathtt{N}}$, or equivalently, $V_P+V_M+V_R\ge 0$. When $k>0$, the condition $V_P+V_M+V_R>0$ holds only if $k>2(2\sqrt{2}-1)$. When $k<0$, the condition holds only if $k\le -2$. Moreover, the equilibrium transfer payment under forecast integration is $T^*=V_M$, which is positive when $k<-2$ and $k>2(2\sqrt{2}-1)$.

The above discussion proves the result. □

EC.1.7. Proof of Proposition 5. In equilibrium, the platform's net profit is given by $\Pi_P^{\mathtt{N}} = 2(\frac{(u-c)^2}{(k+6)^2} + \frac{(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2}{16}\eta)$ if $-2 \le k \le 2(2\sqrt{2}-1)$, where $\Pi_P^{\mathtt{N}}$ is decreasing in k. Otherwise, the platform's net profit is:

$$\tilde{\Pi}_P^{\mathtt{I}} = \Pi_P^{\mathtt{I}} + V_M + V_R = \frac{64(u-c)^2 + (k^3+10k^2+28k+88)\eta(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2}{32(k+6)^2}.$$

Moreover, if $\eta > \frac{(u-c)^2}{2(\sqrt{2}+1)(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2}$, then $\tilde{\Pi}_P^{\mathtt{I}}$ is first decreasing and then increasing in $k \in [-2, 2(2\sqrt{2}-1)]$; otherwise, it is decreasing in $k \in [-2, 2(2\sqrt{2}-1)]$. As a result, the platform's net profit is first decreasing and then increasing in k if $\eta > \frac{(u-c)^2}{2(\sqrt{2}+1)(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2}$, otherwise , it is decreasing in k.

EC.1.8. Proof of Lemma 1. Recall that $u(\beta) = a - r_C - \beta\rho\sigma^2 - (\alpha+\beta s)(v+\rho s-r_C)$. Without forecast integration, the retailer's and the supply chain's expected profits are given by: $\Pi_R^{\mathtt{N}} = \frac{(u(\cdot)-c)^2}{(k+6)^2} + \frac{(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2}{16}\eta$ and $\Pi_S^{\mathtt{N}} = \Pi_R^{\mathtt{N}} + \Pi_M^{\mathtt{N}} = \frac{(u(\cdot)-c)^2}{2(k+6)} - \frac{1}{32}\eta(k-2)(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2$. We observe that the term $u(\beta)$ is decreasing in β, while the term $\beta(v+\rho s-r_C)+\rho(\alpha+\beta s)$ is increasing in β. Therefore, for the retailer, we have: $\frac{\partial^2 \Pi_R^{\mathtt{N}}}{\partial \beta^2} > 0$, meaning that $\Pi_R^{\mathtt{N}}$ is first decreasing and then increasing in β with a minimum point $\hat{\beta}_R^{\mathtt{N}} < +\infty$. For the supply chain, when $k > 2$, $\Pi_S^{\mathtt{N}}$ decreases in β, or equivalently, first decreasing and then increasing in β with a minimum point $\hat{\beta}^{\mathtt{N}} = +\infty$; when $k < 2$, we have: $\frac{\partial^2 \Pi_S^{\mathtt{N}}}{\partial \beta^2} > 0$, meaning that $\Pi_S^{\mathtt{N}}$ is first decreasing and then increasing in β with a minimum point $\hat{\beta}^{\mathtt{N}} < +\infty$.

With forecast integration, the retailer's and the supply chain's expected profits are given by: $\Pi_R^{\mathtt{I}} = \frac{(u(\cdot)-c)^2}{(k+6)^2} + \frac{(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2}{(k+6)^2}\eta$ and $\Pi_S^{\mathtt{I}} = \Pi_R^{\mathtt{I}} + \Pi_M^{\mathtt{I}} = \frac{(u(\cdot)-c)^2+\eta(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2}{2(k+6)}$. Following the same steps, we obtain $\Pi_R^{\mathtt{I}}$ is first decreasing and then increasing in β with a minimum point $\hat{\beta}_R^{\mathtt{I}} < +\infty$, and so is $\Pi_S^{\mathtt{I}}$ with a minimum point $\hat{\beta}^{\mathtt{I}} < +\infty$. □

EC.1.9. Proof of Proposition 6. To prove the result, let $\tilde{\Pi}_R$ and $\tilde{\Pi}_{SC}$ denote the retailer's and supply chain's and system's net profits, which can be rewritten as follows: $\Pi_R^i = \frac{1}{(k+6)^2}[(u(\cdot)-c)^2 + a_R^i\eta(\beta(v+\rho s - r_C)+\rho(\alpha+\beta s)))^2]$ and $\tilde{\Pi}_{SC} = \frac{1}{2(k+6)}[(u(\cdot)-c)^2 + a_{SC}^i\eta(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2]$, where $a_R^{\mathtt{N}} = \frac{(k+6)^2}{16}$, $a_R^{\mathtt{I}} = 1$, $a_{SC}^{\mathtt{N}} = -\frac{(k+6)(k-2)}{16}$, and $a_S^{\mathtt{I}} = 1$. In addition, we have the following properties: (a) $a_R^{\mathtt{N}} < a_R^{\mathtt{I}}$ if $k < -2$, and $a_R^{\mathtt{N}} > a_R^{\mathtt{I}}$ otherwise; (b) $a_{SC}^{\mathtt{N}} < a_{SC}^{\mathtt{I}}$; (c) $a_{SC}^{\mathtt{N}} < 0$ for $k > 2$.

Note that for each profit function, its minimum point is equivalent to the minimum point for the inner function $\pi_j^i(\beta) = (u(\cdot)-c)^2 + a_j^i\eta(\alpha\rho+\beta(-r_C+2\rho s+v))^2$, where $j \in \{R, SC\}$. Moreover, when $a_j^i \le 0$, the inner function $\pi_i(\beta)$ is decreasing in β such that the minimum point is actually $+\infty$. When $a_j^i > 0$, the minimum point for the inner function actually decreases with a_j^i. The above discussion proves the result. □

EC.2. Proof of Results in Section 4

EC.2.1. Proof of Results in Section 4.1. Taking the logarithm of the objective in (22) yields $\theta\ln(V_R - P + T) + (1-\theta)\ln(V_M - T)$. We differentiate it with respect to T and set the derivative to zero to obtain the first-order condition as $\frac{\theta}{V_R-P+T} - \frac{1-\theta}{V_M-T} = 0$. We solve this and obtain the equilibrium transfer payment $T = -\theta V_M - (1-\theta)(V_R - P)$. It then follows that the retailer's value from forecast integration is $V_R - P + T = V_R - P - \theta V_M - (1-\theta)(V_R - P) = \theta(V_R + V_M - P)$, and the manufacturer's value is $V_M - T = \Pi_M^{\mathtt{N}} + (1-\theta)(V_R + V_M - P)$. Forecast integration is adopted iff it provides non-negative value to both the manufacturer and the retailer, or equivalently, $V_R + V_M - P \ge 0$. Since this condition is identical to that in the main model, the equilibrium adoption of forecast integration, transfer payment, and equilibrium net profits follow directly from Proposition 4. We omit the detailed analysis here to avoid repetition. □

EC.2.2. Proof of Proposition 7. Define $\beta := \lambda/r_C$ as the effective probability of freight rejection. Recall that the retailer's net expected profit either with or without forecast integration is $\Pi_R^{\mathtt{N}} = \frac{(u(\beta)-c)^2}{(k+6)^2} + \frac{1}{16}\eta(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2$ and $\Pi_M^{\mathtt{N}} = \frac{(k+4)(u(\beta)-c)^2}{2(k+6)^2} - \frac{1}{32}\eta k(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2$. For the retailer, since $\frac{(u(\beta)-c)^2}{(k+6)^2}$ decreases in β, $\frac{1}{16}\eta(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2$ increases in β and $\partial^2\Pi_R^{\mathtt{N}}/\partial\beta^2 > 0$, we claim that $\Pi_R^{\mathtt{N}}$ is convex in β.

For the manufacturer, when $k > 0$, $\Pi_M^{\mathtt{N}}$ is decreasing in β; while, when $k < 0$, we have $\partial^2\Pi_M^{\mathtt{N}}/\partial\beta^2 > 0$ and $\Pi_M^{\mathtt{N}}$ is convex in β.

For the platform, its net profit is $\frac{2(u(\beta)-c)^2}{(k+6)^2} + \frac{1}{8}\eta(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2$ without integration and becomes $\frac{2(u(\beta)-c)^2}{(k+6)^2} + \frac{\eta(k(k(k+10)+28)+88)(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s)))^2}{32(k+6)^2}$.

In each case, we have the platform's net profit is convex in β. Moreover, let $\tilde{\beta}^{\mathtt{N}}$ and $\tilde{\beta}^{\mathtt{I}}$ denote the minimum points for the platform's net profits without and with forecast integration. Then, we have $\tilde{\beta}^{\mathtt{N}} > \tilde{\beta}^{\mathtt{I}}$ with adoption (i.e., $k > 2(2\sqrt{2}-1)$ or $k < -2$). This means that forecast integration expands the region over which the platform's net profit increases.

Based on the above discussion, we prove Proposition 7. □

EC.3. Proof of Results in Section 5

We first summarize definition of new parameters used in this section below.

Table EC.1 Parameter definition

Panel A: Parameters in retail quantity expressions			
(Υ_i, Υ_j)	$\phi_{i0}^{\Upsilon_i,\Upsilon_j}$	$\phi_{i1}^{\Upsilon_i,\Upsilon_j}$	$\phi_{i2}^{\Upsilon_i,\Upsilon_j}$
$(\mathtt{I},\mathtt{I})$	$\frac{\beta\rho}{\gamma+k+6}$	$-\frac{(v+\rho s-r_C)\beta+\rho(\alpha+\beta s)}{\gamma+k+6}$	$-\frac{\beta\rho}{\gamma+k+6}$
$(\mathtt{I},\mathtt{N})$	$\frac{\beta\rho(4-\gamma)}{24-\gamma^2+4k}$	$-\frac{(4-\gamma)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))}{24-\gamma^2+4k}$	$-\frac{\beta\rho(4-\gamma)}{24-\gamma^2+4k}$
$(\mathtt{N},\mathtt{I})$	$\frac{\beta\rho(6-\gamma+k)}{24-\gamma^2+4k}$	$-\frac{(6-\gamma+k)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))}{24-\gamma^2+4k}$	$-\frac{\beta\rho(6-\gamma+k)}{24-\gamma^2+4k}$
$(\mathtt{N},\mathtt{N})$	$\frac{\beta\rho}{\gamma+4}$	$-\frac{(v+\rho s-r_C)\beta+\rho(\alpha+\beta s)}{\gamma+4}$	$-\frac{\beta\rho}{\gamma+4}$
Panel B: Parameters in profit expressions			
(Υ_i, Υ_j)	$\varphi_R^{\Upsilon_i,\Upsilon_j}$	$\varphi_M^{\Upsilon_i,\Upsilon_j}$	$\varphi_P^{\Upsilon_i,\Upsilon_j}$
$(\mathtt{I},\mathtt{N})$	$\frac{(4-\gamma)^2}{(4k+24-\gamma^2)^2}$	$\frac{(4-\gamma)^2(k+4)}{2(4k+24-\gamma^2)^2}$	$2\varphi_R^{\mathtt{I},\mathtt{N}}$
$(\mathtt{N},\mathtt{N})$	$\frac{1}{(\gamma+4)^2}$	$-\frac{k}{2(\gamma+4)^2}$	$2\varphi_R^{\mathtt{N},\mathtt{N}}$
$(\mathtt{I},\mathtt{I})$	$\frac{1}{(\gamma+k+6)^2}$	$\frac{k+4}{2(\gamma+k+6)^2}$	$2\varphi_R^{\mathtt{I},\mathtt{I}}$
$(\mathtt{N},\mathtt{I})$	$\frac{(6-\gamma+k)^2}{(4k+24-\gamma^2)^2}$	$-\frac{k(6-\gamma+k)^2}{2(4k+24-\gamma^2)^2}$	$2\varphi_R^{\mathtt{N},\mathtt{I}}$
Panel C: Parameters in forecast integration value expressions			
$h^{\mathtt{N}} := \frac{(k+2)(\gamma^4+4(k+6)(4-\gamma^2+2k))}{(\gamma+4)^2(4(k+6)-\gamma^2)^2}$		$h^{\mathtt{I}} := \frac{(k+2)(2\gamma^4-2\gamma^2(k+6)^2+(k+2)(k+6)^3)}{2(\gamma+k+6)^2(4(k+6)-\gamma^2)^2}$	

EC.3.1. Derivation of Equilibrium Outcomes. For competing supply chains, we derive their equilibrium retail quantities as follows. Given the common conjecture q_j, we follow the analysis from the single supply chain setting (see the proof of Proposition 1) to derive the wholesale price and the platform's freight rate under no integration, denoted by $w_i^{\mathtt{N}}(q_j)$ and $r_i^{\mathtt{N}}(q_j)$, respectively:

$$w_i^{\mathtt{N}}(q_j) = w^b - \frac{\gamma(k+2)\mathtt{E}[q_j]}{k+6}, \tag{EC-5}$$

$$r_i^{\mathtt{N}}(q_j) = \frac{r^b\mathtt{E}[\delta(S)] + \frac{\beta(r_C+v)+\rho(\alpha+2\beta s)}{2}\mathtt{E}[\epsilon \mid \xi] + \frac{\beta\rho}{2}\left(\mathtt{E}[\epsilon^2 \mid \xi] - \sigma^2\right) + \frac{\gamma}{2}\left(\frac{k+2}{k+6}\mathtt{E}[q_j] - \mathtt{E}[q_j \mid \xi]\right)}{\mathtt{E}[\delta(S) \mid \xi]}. \tag{EC-6}$$

The retail quantity of supply chain i, denoted by $q_i^{\mathtt{N}}(q_j)$, is:

$$q_i^{\mathtt{N}}(q_j) = q^b - \frac{(v-r_C)\beta + \rho(\alpha+2\beta s)}{4}\mathtt{E}[\epsilon \mid \xi] - \frac{1}{4}\beta\rho\left(\mathtt{E}[\epsilon^2 \mid \xi] - \sigma^2\right) - \frac{\gamma}{4}\left(\mathtt{E}[q_j \mid \xi] - \frac{k+2}{k+6}\mathtt{E}[q_j]\right). \tag{EC-7}$$

Similarly, under integration, the wholesale price and freight rate, denoted by $w_i^{\mathtt{I}}(q_j)$ and $r_i^{\mathtt{I}}(q_j)$, are given by:

$$w_i^{\mathtt{I}}(q_j) = w^b - \frac{(k+2)((v+\rho s - r_C)\beta + \rho(\alpha+\beta s))\mathtt{E}[\epsilon \mid \xi]}{k+6} - \frac{(k+2)\rho\beta\left(\mathtt{E}[\epsilon^2 \mid \xi] - \sigma^2\right)}{k+6} - \frac{\gamma(k+2)\mathtt{E}[q_j \mid \xi]}{k+6}, \tag{EC-8}$$

$$r_i^{\mathtt{I}}(q_j) = \frac{r^b\mathtt{E}[\delta(S)] + \frac{(k+4)(\rho(\alpha+2\beta s)+\beta v)+2\beta r_C}{k+6}\mathtt{E}[\epsilon \mid \xi] + \frac{\beta(k+4)\rho}{k+6}\left(\mathtt{E}[\epsilon^2 \mid \xi] - \sigma^2\right) - \frac{2\gamma}{k+6}\mathtt{E}[q_j|\xi]}{\mathtt{E}[\delta(S)|\xi]}. \tag{EC-9}$$

The corresponding retail quantity is:

$$q_i^{\mathtt{I}}(q_j) = q^b - \frac{(v-r_C)\beta + \rho(\alpha+2\beta s)}{k+6}\mathtt{E}[\epsilon \mid \xi] - \frac{\beta\rho(\mathtt{E}[\epsilon^2 \mid \xi] - \sigma^2)}{k+6} - \frac{\gamma\mathtt{E}[q_j|\xi]}{k+6}. \tag{EC-10}$$

Based on $q_i^{\mathtt{N}}(q_j)$ and $q_i^{\mathtt{I}}(q_j)$ in (EC-7) and (EC-10), we derive the equilibrium retail quantities. First, consider the case in which both retailers do not adopt forecast integration (i.e., $\Upsilon_i = \Upsilon_j = \mathtt{N}$). In this case, it is straightforward to verify that the pair $(q_i^{\mathtt{NN}}, q_j^{\mathtt{NN}})$ satisfies the consistency conditions $q_i^{\mathtt{NN}} = q_i^{\mathtt{N}}(q_j^{\mathtt{NN}})$ and $q_j^{\mathtt{NN}} = q_j^{\mathtt{N}}(q_i^{\mathtt{NN}})$. Moreover, by applying Claim 1 in Ha et al. (2011), uniqueness follows.

Substituting $q_j^{\mathtt{NN}}$ into $w_i^{\mathtt{N}}(\cdot)$ and $r_i^{\mathtt{N}}(\cdot)$ yields the equilibrium wholesale price and freight rate. The equilibrium outcomes under other forecast arrangements can be derived analogously.

Second, we derive the expected profits for all players. Specifically, given rival supply chain j's retail quantity $q_j^{\Upsilon_j,\Upsilon_i} = \frac{u-c}{\gamma+k+6} + \phi_{j0}^{\Upsilon_j,\Upsilon_i}\sigma^2 + \phi_{j1}^{\Upsilon_j,\Upsilon_i}\mathtt{E}[\epsilon \mid \xi] + \phi_{j2}^{\Upsilon_j,\Upsilon_i}\mathtt{E}[\epsilon^2 \mid \xi]$, the market-clearing price for retailer i can be rewritten as $p_i = (a - \gamma q_j^{\Upsilon_j,\Upsilon_i}) - q_i = \hat{a}(\boldsymbol{\phi}_j^{\Upsilon_j,\Upsilon_i}) - q_i$, where $\hat{a}(\boldsymbol{\phi}_j^{\Upsilon_j,\Upsilon_i}) = a - \gamma\left(\frac{u-c}{\gamma+k+6} + \phi_{j0}^{\Upsilon_j,\Upsilon_i}\sigma^2 + \phi_{j1}^{\Upsilon_j,\Upsilon_i}\mathtt{E}[\epsilon \mid \xi] + \phi_{j2}^{\Upsilon_j,\Upsilon_i}\mathtt{E}[\epsilon^2 \mid \xi]\right)$ denotes the potential market size of supply chain i, which is a function of $\boldsymbol{\phi}_j^{\Upsilon_j,\Upsilon_i} = \{\phi_{j0}^{\Upsilon_j,\Upsilon_i}, \phi_{j1}^{\Upsilon_j,\Upsilon_i}, \phi_{j2}^{\Upsilon_j,\Upsilon_i}\}$ capturing the competitive response of rival supply chain j.

Following the analysis for a single supply chain, let $\Pi_{R_i}^{\mathtt{N}}(\boldsymbol{\phi}_j^{\Upsilon_j,\mathtt{N}})$ and $\Pi_{M_i}^{\mathtt{N}}(\boldsymbol{\phi}_j^{\Upsilon_j,\mathtt{N}})$ denote the expected profits of retailer i and manufacturer i, respectively, and let $\Pi_{P_i}^{\mathtt{N}}(\boldsymbol{\phi}_j^{\Upsilon_j,\mathtt{N}})$ denote the platform's expected profit from serving retailer i. We consider the following cases:

(a) When rival supply chain j does not adopt forecast integration: If focal supply chain i does not adopt, the expected profits are $\Pi_{R_i}^{\mathtt{NN}} = \Pi_{R_i}^{\mathtt{N}}(\boldsymbol{\phi}_j^{\mathtt{NN}}) = \Pi_R^{bc} + \frac{\eta((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{(\gamma+4)^2}$, $\Pi_{P_i}^{\mathtt{NN}} = 2\Pi_{R_i}^{\mathtt{NN}}$ and $\Pi_{M_i}^{\mathtt{NN}} = \Pi_{M_i}^{\mathtt{N}}(\boldsymbol{\phi}_j^{\mathtt{NN}}) = \Pi_M^{bc} - \frac{\eta k((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{2(\gamma+4)^2}$; If supply chain i adopts, the expected profits are $\Pi_{R_i}^{\mathtt{IN}} = \Pi_{R_i}^{\mathtt{I}}(\boldsymbol{\phi}_j^{\mathtt{NI}}) = \Pi_R^{bc} + \frac{(4-\gamma)^2\eta((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{(\gamma^2-4(k+6))^2}$, $\Pi_{P_i}^{\mathtt{IN}} = 2\Pi_{R_i}^{\mathtt{IN}}$ and $\Pi_{M_i}^{\mathtt{IN}} = \Pi_{M_i}^{\mathtt{I}}(\boldsymbol{\phi}_j^{\mathtt{NI}}) = \Pi_M^{bc} + \frac{(4-\gamma)^2\eta(k+4)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{2(\gamma^2-4(k+6))^2}$.

(b) When rival supply chain j adopts forecast integration: If supply chain i does not adopt, the expected profits are $\Pi^{\mathtt{NI}}_{R_i} = \Pi^{\mathtt{N}}_{R_i}(\boldsymbol{\phi}^{\mathtt{IN}}_j) = \Pi^{bc}_R + \frac{\eta(-\gamma+k+6)^2((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{(\gamma^2-4(k+6))^2}$, $\Pi^{\mathtt{NI}}_{P_i} = 2\Pi^{\mathtt{NI}}_{R_i}$ and $\Pi^{\mathtt{NI}}_{M_i} = \Pi^{\mathtt{N}}_{M_i}(\boldsymbol{\phi}^{\mathtt{IN}}_j) = \Pi^{bc}_M - \frac{\eta k(-\gamma+k+6)^2((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{2(\gamma^2-4(k+6))^2}$; If supply chain i adopts, the expected profits are $\Pi^{\mathtt{II}}_{R_i} = \Pi^{\mathtt{I}}_{R_i}(\boldsymbol{\phi}^{\mathtt{II}}_j) = \Pi^{bc}_R + \frac{\eta((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{(\gamma+k+6)^2}$, $\Pi^{\mathtt{II}}_{P_i} = 2\Pi^{\mathtt{II}}_{R_i}$ and $\Pi^{\mathtt{II}}_{M_i} = \Pi^{\mathtt{I}}_{M_i}(\boldsymbol{\phi}^{\mathtt{II}}_j) = \Pi^{bc}_M + \frac{\eta(k+4)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{2(\gamma+k+6)^2}$.

EC.3.2. Proof of Proposition 8. Part (i) is a direct result of Section EC.3.1. Here, we focus on proving (ii) and (iii) as follows.

(a) When rival supply chain j does not adopt forecast integration, the value of forecast integration for retailer i is $V^{\mathtt{N}}_{R_i} = -\frac{8\eta(k+2)\left(20-\gamma^2+2k\right)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{(\gamma+4)^2(\gamma^2-4(k+6))^2}$, for the platform it is $V^{\mathtt{N}}_{P_i} = 2V^{\mathtt{N}}_{R_i}$, and for manufacturer i it is $V^{\mathtt{N}}_{M_i} = \frac{\eta(k+2)\left(\gamma^4-4\gamma^2(k+8)+8k(k+10)+256\right)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{(\gamma+4)^2(\gamma^2-4(k+6))^2}$. Thus, if $k > -2$, then $V^{\mathtt{N}}_{R_i} < 0$, $V^{\mathtt{N}}_{P_i} < 0$, and $V^{\mathtt{N}}_{M_i} > 0$; if $k < -2$, then $V^{\mathtt{N}}_{R_i} > 0$, $V^{\mathtt{N}}_{P_i} > 0$, and $V^{\mathtt{N}}_{M_i} < 0$. The total value of forecast integration for supply chain i is $V^{\mathtt{N}}_{R_i} + V^{\mathtt{N}}_{M_i} = \frac{\eta(k+2)\left(\gamma^4-4\gamma^2(k+6)+8(k+2)(k+6)\right)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{(\gamma+4)^2(\gamma^2-4(k+6))^2} = h^{\mathtt{N}}((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2\eta$, where $h^{\mathtt{N}} = \frac{(k+2)\left(\gamma^4-4\gamma^2(k+6)+8(k+2)(k+6)\right)}{(\gamma+4)^2(4(k+6)-\gamma^2)^2} \geq 0$.

(b) When rival supply chain j adopts forecast integration, the value of forecast integration for retailer i is $V^{\mathtt{I}}_{R_i} = -\frac{\eta(k+2)(k+6)\left(60-2\gamma^2+k(k+16)\right)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{(\gamma+k+6)^2(\gamma^2-4(k+6))^2}$, for the platform it is $V^{\mathtt{I}}_{P_i} = 2V^{\mathtt{I}}_{R_i}$, and for manufacturer i it is $V^{\mathtt{I}}_{M_i} = \frac{\eta(k+2)\left(2\gamma^4-2\gamma^2(k+6)(k+8)+(k+6)^2(k(k+10)+32)\right)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{2(\gamma+k+6)^2(\gamma^2-4(k+6))^2}$. Thus, if $k > -2$, then $V^{\mathtt{I}}_{R_i} < 0$, $V^{\mathtt{I}}_{P_i} < 0$, and $V^{\mathtt{I}}_{M_i} > 0$; if $k < -2$, then $V^{\mathtt{I}}_{R_i} > 0$, $V^{\mathtt{I}}_{P_i} > 0$, and $V^{\mathtt{I}}_{M_i} < 0$. The total value of forecast integration for supply chain i is $V^{\mathtt{I}}_{R_i} + V^{\mathtt{I}}_{M_i} = \frac{\eta(k+2)\left(2\gamma^4-2\gamma^2(k+6)^2+(k+2)(k+6)^3\right)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{2(\gamma+k+6)^2(\gamma^2-4(k+6))^2} = h^{\mathtt{I}}((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2\eta$, where $h^{\mathtt{I}} = \frac{(k+2)\left(2\gamma^4-2\gamma^2(k+6)^2+(k+2)(k+6)^3\right)}{2(\gamma+k+6)^2(4(k+6)-\gamma^2)^2} \geq 0$.

Moreover, the parameters $h^{\mathtt{N}}$ and $h^{\mathtt{I}}$ satisfy $h^{\mathtt{N}} \geq 0$, $h^{\mathtt{I}} \geq 0$, and $h^{\mathtt{I}} > h^{\mathtt{N}}$ if $k > -2$, while $h^{\mathtt{I}} < h^{\mathtt{N}}$ if $k < -2$.

The above discussion proves the proposition. □

EC.3.3. Proof of Proposition 9. To prove the result, we first characterize the equilibrium adoption of forecast integration by competing supply chains for any given access price P in the following lemma.

LEMMA EC.1. *For competing supply chains, given any access price P, the adoption of forecast integration is characterized as follows:*

(i) When $k > -2$, if $P \leq h^{\mathtt{I}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then both supply chains will adopt forecast integration; if $P > h^{\mathtt{I}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then both supply chains will not adopt forecast integration.

(ii) When $k < -2$, if $P \leq h^{\mathtt{I}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then both supply chains will adopt forecast integration; if $h^{\mathtt{I}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta < P \leq h^{\mathtt{N}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then one supply chain will adopt forecast integration while the other will not; if $P > h^{\mathtt{N}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then both supply chains will not adopt forecast integration.

Proof of Lemma EC.1 Based on Proposition 8, we proceed as follows.

(a) When $k > -2$, we have $h^{\mathtt{I}} > h^{\mathtt{N}}$. If $P \leq h^{\mathtt{N}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then each supply chain i will adopt forecast integration regardless of the forecast arrangement of rival supply chain j; thus, both supply chains adopt, i.e., $(\mathtt{I},\mathtt{I})$ is the unique equilibrium. If $h^{\mathtt{N}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta \leq P \leq h^{\mathtt{I}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then supply chain i adopts forecast integration when rival supply chain j adopts forecast integration, and it adopts SIS when the rival adopts no integration. In this case, $(\mathtt{I},\mathtt{I})$ and $(\mathtt{N},\mathtt{N})$ are two possible equilibria, with $(\mathtt{I},\mathtt{I})$ being Pareto optimal. If $P > h^{\mathtt{I}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then each supply chain i will not adopt forecast integration regardless of the rival's choice; thus, both supply chains do not adopt, i.e., $(\mathtt{N},\mathtt{N})$ is the unique equilibrium.

(b) When $k<-2$, we have $h^{\mathtt{N}}>h^{\mathtt{I}}$. If $P\le h^{\mathtt{I}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then each supply chain i will adopt forecast integration regardless of the forecast arrangement of rival supply chain j; thus, both supply chains adopt, i.e., $(\mathtt{I},\mathtt{I})$ is the unique equilibrium. If $h^{\mathtt{I}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta\le P\le h^{\mathtt{N}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then supply chain i does not adopt forecast integration when rival supply chain j adopts forecast integration, and it adopts forecast integration when the rival does not adopt. In this case, $(\mathtt{I},\mathtt{N})$ and $(\mathtt{N},\mathtt{I})$ are two possible equilibria. If $P>h^{\mathtt{N}}(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s))^2\eta$, then each supply chain i will not adopt forecast integration regardless of the rival's choice; thus, both supply chains do not adopt, i.e., $(\mathtt{N},\mathtt{N})$ is the unique equilibrium. □

Building on Lemma EC.1, we first prove Proposition 9(i) as follows: (a) When $k>0$, if both supply chains adopt forecast integration, the platform's net profit—accounting for the optimal access price—is $\sum_{i=1}^{2}\Pi_{P_i}^{\mathtt{II}}+2h^{\mathtt{I}}((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2\eta$; if neither supply chain adopts, its net profit is $\sum_{i=1}^{2}\Pi_{P_i}^{\mathtt{NN}}$. The profit difference is then calculated as $\sum_{i=1}^{2}\Pi_{P_i}^{\mathtt{II}}-\sum_{i=1}^{2}\Pi_{P_i}^{\mathtt{NN}}+2P^*=\frac{(k+2)((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2}{(\gamma+k+6)^2}\eta g(k,\gamma)$, where $g(k,\gamma):=\frac{2\gamma^4-2\gamma^2(k+6)^2+(k+2)(k+6)^3}{(\gamma^2-4(k+6))^2}-\frac{4(2(\gamma+5)+k)}{(\gamma+4)^2}$. Thus, both supply chains will adopt forecast integration in equilibrium if $g(k,\gamma)\ge 0$. Note that $g(\cdot)$ is increasing in γ; as such, $\bar{k}$ decreases with γ. (b) When $0>k>-2$, the platform faces the choice between both supply chains adopting forecast integration and neither adopting it. In this scenario, the profit difference between the two options is $((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2\eta g(k,\gamma)<0$, since $g(k,\gamma)<0$ in this range. Thus, neither supply chain will adopt in equilibrium. (c) When $k<-2$, we analyze the platform's choice among three options: (i) both supply chains adopt forecast integration; (ii) neither adopts forecast integration; (iii) one supply chain adopts while the other does not. We compare their profits as follows: The profit difference between options (i) and (ii) is $((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2\eta g(k,\gamma)>0$, since $g(k,\gamma)>0$. The profit difference between options (iii) and (ii) is $((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2\eta g_1(k,\gamma)>0$, where $g_1(k,\gamma):=\frac{(k+2)\left(\gamma^4-4\gamma^2(k+2)+8k(k+4)-224\right)}{(\gamma+4)^2(\gamma^2-4(k+6))^2}>0$. Finally, the profit difference between options (i) and (iii) is $((v+\rho s-r_C)\beta+\rho(\alpha+\beta s))^2\eta\,(g(k,\gamma)-g_1(k,\gamma))>0$. Accordingly, both competing supply chains will adopt forecast integration in equilibrium when $k<-2$.

Given the above conditions, we discuss the impact of changing β on each retailer's and supply chain's profits as follows. (a) When $-2\le k\le\bar{k}$, each retailer's profit is $\Pi_{R_i}^{\mathtt{NN}}=\Pi_R^{bc}(\beta)+\varphi_R^{\mathtt{NN}}\big(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s)\big)^2\eta$, which is first decreasing and then increasing in β with a finite minimum point. And each supply chain's profit is $\Pi_{R_i}^{\mathtt{NN}}+\Pi_{M_i}^{\mathtt{NN}}=\Pi_R^{bc}(\beta)+\Pi_M^{bc}(\beta)+(\varphi_R^{\mathtt{NN}}+\varphi_M^{\mathtt{NN}})\big(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s)\big)^2\eta)$, where $(\varphi_R^{\mathtt{NN}}+\varphi_M^{\mathtt{NN}})=\frac{(2-k)}{(\gamma+4)^2}$ is positive when $k<2$. As such, each supply chain's profit is first decreasing and then increasing in β with a finite minimum point when $k<2$, and it is decreasing, or equivalently first decreasing and then increasing with an infinite minimum point$(=\infty)$, when $k>2$. (b) When $k>\bar{k}$ or $k<-2$, each retailer's profit is $\Pi_{R_i}^{\mathtt{II}}=\Pi_R^{bc}(\beta)+\varphi_R^{\mathtt{II}}\big(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s)\big)^2\eta$, which is first decreasing and increasing in β with a finite minimum point. And each supply chain profit's profit is $\Pi_{R_i}^{\mathtt{II}}+\Pi_{M_i}^{\mathtt{II}}=\Pi_R^{bc}(\beta)+\Pi_M^{bc}(\beta)+(\varphi_R^{\mathtt{II}}+\varphi_M^{\mathtt{II}})\big(\beta(v+\rho s-r_C)+\rho(\alpha+\beta s)\big)^2\eta)$, where $(\varphi_R^{\mathtt{II}}+\varphi_M^{\mathtt{II}})=\frac{(k+6)}{2(\gamma+k+6)^2}>0$. As such, each supply chain's profit is first decreasing and then increasing with a finite minimum point.

The above discussion proves the result. □