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Cooperation Partnerships in Live-Stream E-Commerce: Optimal Selection for Brand Manufacturers

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Abstract

Live-streaming commerce has become a critical information channel through which consumers evaluate products and make purchase decisions, yet brand manufacturers face substantial uncertainty when selecting live-streaming partners. This study investigates how streamer influence and consumer sensitivity to live-streaming service quality jointly shape optimal cooperation structures in platform-based commerce. We develop a game-theoretic decision framework comparing three cooperation modes—Nash negotiation, manufacturer-led, and streamer-led—and derive closed-form equilibria for pricing, service quality, and profit allocation. The results show that manufacturer-led cooperation consistently maximizes brand profit by preserving incentives to provide service quality. In contrast, streamer-led cooperation can reduce overall efficiency when dominant streamers lack motivation to improve service quality. To corroborate our theoretical predictions, we employ live-stream sales data from the Douyin (TikTok) platform, covering multiple streamer tiers and two cosmetic brands, and find empirical support for the model's key insights. The findings contribute to the literature on information processing and incentive alignment in platform-based live-streaming commerce, offering actionable guidance for manufacturers' partnership strategies.

Keywords: cooperation strategy; live-stream commerce; pricing; game theory

1. Introduction

The rapid advancement of mobile internet and streaming technologies has significantly reshaped commercial activities, transforming how firms engage consumers and how consumers search for and purchase products. By leveraging real-time interaction, personalized communication, and enhanced consumer engagement, live-stream selling has emerged as one of the fastest-growing digital retail formats. The COVID-19 pandemic further accelerated the adoption of live-stream commerce, driving its transition from an emerging marketing tool to a mainstream retail channel. As a result, more manufacturers have incorporated live-stream selling into their omnichannel strategies. In China, live-stream commerce has developed into a multi-trillion-yuan industry, involving hundreds of millions of consumers and millions of content creators. Influential streamers such as Luo Yonghao and Dong Yuhui generate remarkable sales volumes, while leading e-commerce

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platforms, including Amazon, JD.com, Taobao, and TikTok, have integrated live-streaming to boost customer engagement and strengthen competitive advantage [1].

Although live-stream selling has become an effective business model for stimulating consumer demand, it does not necessarily improve firm performance. Manufacturers therefore face a fundamental strategic challenge: how should they select live-stream partners and design a cooperation strategy to maximize profitability while maintaining efficient channel governance? To address this issue, this study investigates strategic interactions between manufacturers and streamers in live-streaming commerce through a game-theoretic framework, and the study pursues four research objectives.

Firstly, we compare three alternative cooperation structures, i.e., Nash bargaining, manufacturer-led governance, and streamer-led governance, to identify the optimal collaboration strategy under different market conditions. Secondly, we examine how streamer characteristics, particularly market influence and service quality, affect pricing decisions, commission allocation, service investment, and profit distribution between manufacturers and streamers. Thirdly, we investigate how consumers' sensitivity to streamer influence and service quality shapes market demand and determines the optimal cooperation structure. Finally, we validate the theoretical predictions using live-stream transaction data collected from the Douyin (TikTok) platform and assess the practical implications of the proposed cooperation strategies. By integrating analytical modeling with empirical evidence, this study provides a comprehensive understanding of channel governance and strategic cooperation in live-streaming commerce.

Studies mainly investigate influencer selection, channel adoption, or contract design under predetermined governance structures. However, little is known about how cooperation governance, streamer influence, and consumers' responsiveness to live-stream service quality jointly determine optimal partnership strategies. This omission limits our understanding of why different cooperation structures coexist in practice and under what market conditions each governance mode becomes optimal.

The structure of this paper is as follows. Section 2 surveys the relevant literature and highlights the study's contributions. Section 3 details the model's framework. Section 4 introduces three strategy models: the Nash negotiation strategy, the brand manufacturer-led strategy, and the streamer-led strategy. Section 5 examines how consumer behavior drives strategy selection. Section 6 evaluates the proposed strategies using empirical data. Section 7 provides concluding remarks and discusses several limitations. All proofs are provided in Appendix A.

2. Literature Review

Live-streaming e-commerce as a new marketing method has rapidly developed and garnered significant attention in recent years. Here, we review the most relevant literature on this topic.

2.1. Channel Strategy

With the rapid development of Internet retailing, a substantial body of research has examined retail channel structures, pricing strategies, and channel integration in e-commerce environments [2–6]. Existing studies have primarily focused on manufacturers' channel expansion decisions, the integration of online and offline channels, and consumers' channel preferences. For example, Chiang et al. [2] investigate whether manufacturers should establish direct online channels to compete with traditional retailers, while Zhang et al. [7] demonstrate that retailers' optimal channel structures depend critically on consumer channel acceptance. Extending this stream of research, Zhou et al. [8] provide a comprehensive review of digital platform channel strategies under both direct and indirect selling modes.

In the context of platform retailing, Shen et al. [9] show that platform-based retail channels can outperform traditional alternatives under specific market conditions. In contrast, Zhang and Hezarkhani [10] examine manufacturers' strategic channel choices across multiple selling formats. Furthermore, Xie et al. [11] show that hybrid channel strategies outperform pure agency selling when supplier capacity is constrained, and Rong et al. [12] reveal that cross-platform multichannel shopping strengthens long-term customer–firm relationships.

Despite these important advances, comparatively little attention has been devoted to manufacturers' collaboration with third-party channels, where strategic interactions between manufacturers and streamers jointly determine pricing, service quality, and commission allocation. In particular, the existing studies rarely consider streamer influence and consumers' sensitivity to service quality. To address these gaps, this study develops a game-theoretic framework to examine manufacturers' strategic selection of live-stream partners and the resulting equilibrium outcomes under alternative cooperation structures.

2.2. Live-Stream Selling Mode

As an emerging digital retail format, live-stream commerce has attracted substantial attention from both practitioners and researchers in recent years [13–16]. Studies have investigated live-stream commerce from multiple perspectives, including channel strategy, pricing decisions, consumer behavior, and platform governance. For example, Cheng et al. [17] evaluate the business value of live-stream commerce by combining econometric analysis with deep learning techniques. Drawing on principal–agent theory, Wang et al. [18] analyze manufacturers' live-stream adoption and pricing decisions, while Zhang and Tang [19] examine whether manufacturers should establish live-stream selling channel using a game-theoretic model. Similarly, Lu and Duan [20] demonstrate that live-stream selling does not necessarily improve firm performance in vertically differentiated markets. Extending this research, Li et al. [21] investigate retailers' optimal buy-online–pickup-in-store (BOPS) strategy under different channel configurations, whereas Chen et al. [22] show that influencer popularity significantly affects commission contracts in brand–influencer collaborations.

With the rapid expansion of live-streaming commerce, recent studies have increasingly focused on strategic interactions among manufacturers, streamers, and consumers. For instance, Ji et al. [23] examine channel selection and pricing decisions in live-stream commerce using a game-theoretic framework, while Zhang et al. [24] demonstrate that manufacturers' live-stream adoption decisions depend on commission rates and signing bonuses. Other studies emphasize the informational role of live-stream selling. For example, Cui et al. [25] show that collaborations between influencers and manufacturers can reduce product return rates and improve product quality, whereas Li et al. [26] find that firms' optimal channel strategies depend on streamer popularity and bargaining power. Beyond analytical modeling, Liu et al. [27] investigate how streamers' linguistic characteristics influence sales performance in online B2B marketplaces, and Chen et al. [28] develop a sales prediction framework by integrating large language models with live-streaming commerce data. In addition, comprehensive reviews of the live-streaming commerce literature have recently been provided by [29–31].

Although most existing studies focus on channel adoption, pricing decisions, or consumer purchase behavior, relatively limited attention has been paid to the joint effects of streamer influence and service quality. This study addresses these gaps by developing a game-theoretic framework that characterizes alternative cooperation structures and identifies the conditions under which different governance mechanisms maximize the performance of both manufacturers and streamers.

2.3. Consumer Behavior

Recognizing that consumer behavior plays a central role in the success of live-stream commerce, researchers have investigated the determinants of purchase intention, customer engagement, and online consumption behavior [32]. Early studies primarily focused on the effects of live-stream content and information quality. For example, Park and Lin [33] examine how the alignment between products and celebrity live-stream content shapes consumer attitudes, while Zhang et al. [34] demonstrate that both product information quality and interaction quality significantly enhance consumers' purchase intentions on live-stream platforms. Building on this line of research, Wongkitrungrueng and Assarut [35] develop a comprehensive framework linking consumers' perceived value of live-stream shopping to purchase intention and engagement.

Recent studies have further explored emerging factors that influence consumer decision-making in live-stream commerce. Using affordance actualization theory, Jia et al. [36] show that AI-generated review summaries improve consumers' perceived credibility through functional affordances. In addition, Gao et al. [37] examine how virtual streamers' characteristics affect consumer responses, while Gong et al. [38] show that self-presentation and live-stream loyalty significantly increase the monetary value of virtual gifts. Other studies emphasize the importance of customer engagement during live-stream interactions. For instance, Huang et al. [39] analyze how interactions between streamers and products influence consumers' purchase intentions and buying behavior, whereas Zheng et al. [40] examine the mechanisms through which customer engagement drives purchasing decisions in live-stream commerce. Related discussions also appear in [41,42].

3. Problem Description and Assumption

A live-streaming commerce (LSC) scenario consists of a brand manufacturer (M) and a streamer (P). The brand manufacturer supplies premium products and reliable post-sale support, while the streamer showcases and promotes the products during live sessions. The audience includes loyal fans who frequently purchase products endorsed by the streamer and casual viewers whose purchasing decisions depend on the streamer's performance. To maximize sales revenue, the brand manufacturer seeks to choose the most suitable streamer for live selling. This study analyzes three collaboration models: Nash negotiation (N-Strategy), manufacturer-led (R-Strategy), and streamer-led (L-Strategy). In the N-Strategy, both parties simultaneously determine marginal revenue, sales commission, and service quality. In the R-Strategy or L-Strategy, one party determines these factors.

In line with risk-sharing and incentive-compatibility principles, the brand manufacturer compensates the streamer with a commission fee for live-streaming sales, consisting of two components: a booth fee based on the streamer's influence and a commission per product sold [43,44]. This payment mechanism is widely adopted. For instance, Ruo Yonghao, a prominent streamer in China with over 10 million fans, receives a fixed booth fee for product display and a 20–30% commission on live-stream sales revenue. In contrast, streamers with fewer than 100,000 fans typically receive only a 0–10% commission. Consistent with this practice, the proposed model assumes the booth fee is $(1+k)\tau$, where k ($0 \leq k \leq 1$) represents the streamer's market influence, including fan loyalty, consumer trust, and persuasive ability. Rather than measuring only follower numbers, this parameter reflects a streamer's overall ability to convert viewers into buyers. It represents the fixed cooperation payment streamers commonly charge before promoting a product. This payment mechanism is widely adopted on platforms such as Douyin and TikTok, where cooperation contracts typically include a fixed appearance fee plus a sales commission.

As established in the prior literature [25,45–47], the sales volume of products in a live-streaming room is defined as $D = a + \mu k + \lambda q - (1-k)p$, where a denotes the actual demand from loyal fans and is normalized to 1 ($a = 1$). The term $\mu k + \lambda q - (1-k)p$ captures the floating demand from onlookers. Here, $\mu k + \lambda q - (1-k)p$ represents the onlookers' sensitivity to the streamer's influence, and μk represents that the onlookers' demand is influenced by the streamer's influence, which means onlookers' buying demand increases with streamer's influence, and can be clearly illustrated from the purchase volume in Ruo's live-stream selling. λ ($0 < \lambda < 1$) represents consumers' responsiveness to live-stream service quality, including product demonstrations, real-time interaction, and information transparency. Following Zhang's [46] and Chen's [47] idea, who assumed that demand depends on both the product price and the streamer's recommendation effort and influence, the term $(1-k)p$ indicates that as the streamer's influence among fans increases, onlookers become less sensitive to price. The price per product is given by $p = w + r$. The cost of the streamer's service quality, which depends on their influence among fans, is defined as $\frac{q^2}{2(1+k)}$, as referred to in [45,46,48].

For the brand manufacturer's decision, the detailed sequence of events is given as follows. First, the brand manufacturer announces a collaboration with a streamer for live-streaming. Second, it chooses the type of streamer to maximize revenue by setting the parameters w, q and r, shown in Figure 1. The parameters involved in this paper are shown in Table 1.

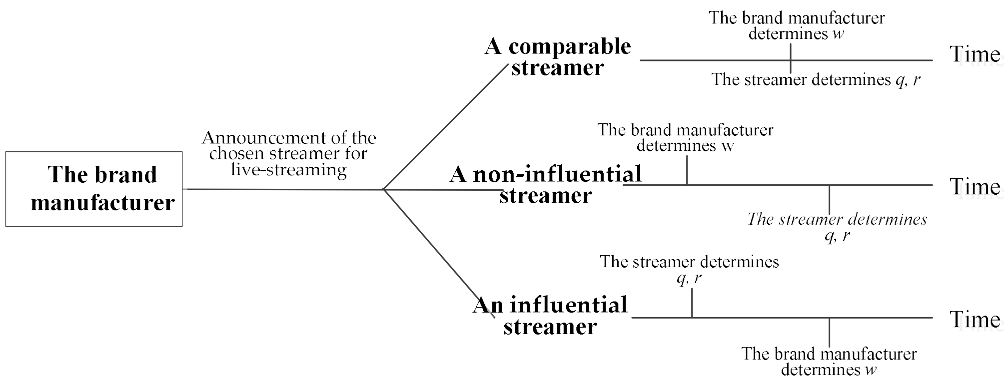


Figure 1. Sequence of events.

Table 1. Summary of notations.

Notation	Description
Parameter	
i	Subscript, $i \in \{M, P\}$, where M, P represents brand manufacturers and streamers, respectively.
j	Subscript, $j \in \{M, P\}$, where M, P represents brand manufacturers and streamers, respectively.
D	Product sales of live-stream selling service system.
k	Streamer's influence among fans, $0 \leq k \leq 1$.
τ	The fixed link fee charged by the brand manufacturer.
λ	Consumer's sensitivity to streamer's service quality in live-stream selling, $0 < \lambda < 1$.
μ	Consumer's sensitivity to streamer's influence among fans, $0 \leq \mu \leq 1$.
Decision variable	
w	Marginal revenue earned by the brand manufacturer per product being sold.
r	Commission obtained by the streamer for selling unit product.
q	Streamer's service quality during live-stream selling.
Derived function	
π_M^j	Total profit of the brand manufacturer under the j-Strategy.
π_M^j	Total profit of the streamer under the j-Strategy.
$*$	The asterisk indicates the optimal outcome.

Based on above description and assumptions, the brand manufacturer and the streamer make decisions to maximize their profits, and the corresponding models are as follows:

$$\max_{w} \pi_M = w(1 + \mu k + \lambda\, q - (1-k)(w+r)) - (1+k)\tau \tag{1}$$

$$\max_{r,q} \pi_P = r(1 + \mu k + \lambda\, q - (1-k)(w+r)) - \frac{q^2}{2(1+k)} + (1+k)\tau \tag{2}$$

4. Model Analysis

4.1. Nash Negotiation Strategy (N-Strategy)

In the Nash negotiation strategy (*N*-Strategy), the brand manufacturer and the streamer have almost equal status among consumers, and they simultaneously make decisions to maximize their benefits in live-stream selling service activities. That is, they independently determine the marginal revenue of the product, commission and live-streaming service quality. Thus, we have

Lemma 1. *Under the N-Strategy, (i) the optimal decision of the brand manufacturer is* $w^{N^*} = \frac{1+\mu k}{3(1-k)-(1+k)\lambda^2}$*, and (ii) the optimal decisions of the streamer are* $r^{N^*} = \frac{1+\mu k}{3(1-k)-(1+k)\lambda^2}$ *and* $q^{N^*} = \frac{\lambda(1+k)(1+\mu k)}{3(1-k)-(1+k)\lambda^2}$.

Substituting w^{N^*}, r^{N^*} and q^{N^*} into functions (1) and (2), the participants' profits are obtained as follows: $\pi_M^{N^*} = \frac{(1-k)(1+\mu k)^2}{3(1-k)-(1+k)\lambda^2} - (1+k)\tau$ and $\pi_P^{N^*} = \frac{(2(1-k)-(1+k)\lambda^2)(1+\mu k)^2}{2(3(1-k)-(1+k)\lambda^2)^2} + (1+k)\tau$.

Lemma 1 shows that the optimal decisions are affected by the parameters λ, μ and k in the same way. When the brand manufacturer adopts the *N*-Strategy in a live-stream selling service system, we have $\frac{\partial x^{N^*}}{\partial \lambda} > 0$, $\frac{\partial x^{N^*}}{\partial \mu} > 0$, $\frac{\partial x^{N^*}}{\partial k} > 0$, where $x \in \{w, r, q\}$. This means both the brand manufacturer and the streamer can lower consumers' price sensitivity by improving the quality of live-streaming services. Further, the streamer can increase their commission and the live-streaming service quality by improving input–output efficiency, which is defined by the sensitivity coefficient of live-streaming service quality and the streamer's influence.

Proposition 1. *Under the N-Strategy, we have (i)* $\frac{\partial \pi_M^{N^*}}{\partial \lambda} > 0$*; (ii) if* $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$*, then* $\frac{\partial \pi_P^{N^*}}{\partial \lambda} > 0$*, and if* $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$*, then* $\frac{\partial \pi_P^{N^*}}{\partial \lambda} \le 0$*; and (iii)* $\frac{\partial \pi_i^{N^*}}{\partial \mu} > 0$, $(i = M, P)$.

Proposition 1 shows that the effect of the consumer's sensitivity to service quality λ and the streamer's influence μ on participants' profit is not uniform under the *N*-Strategy. Specifically, the manufacturer's profit always increases as λ increases. However, the streamer's profit depends on λ: the streamer's profit increases with increasing λ when $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, while it decreases with increasing λ when $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$. Additionally, the conversion rate of onlookers μ positively affects both participants' profits.

4.2. Brand Manufacturer-Led Strategy (R-Strategy)

In a live-stream selling service system, the brand manufacturer takes the leading role while the streamer follows, which creates a Stackelberg game. The brand manufacturer first determines the product's marginal revenue to maximize its profit. Then, the streamer maximizes their profits based on the product's marginal revenue by deciding the unit commission charged to the brand manufacturer and the service quality in live-stream selling activity. This process leads to the following lemma, which can be derived using the inverse method.

Lemma 2. *Under the R-Strategy, (i) the optimal decision of the brand manufacturer is* $w^{R^*} = \frac{1+\mu k}{2(1-k)}$*, and (ii) the optimal decisions of the streamer are* $r^{R^*} = \frac{1+\mu k}{2(2(1-k)-(1+k)\lambda^2)}$ *and* $q^{R^*} = \frac{\lambda(1+k)(1+\mu k)}{2(2(1-k)-(1+k)\lambda^2)}$.

Substituting w^{R^*}, r^{R^*} and q^{R^*} into (1) and (2), the maximum profits of the brand manufacturer and the streamer are obtained as follows: $\pi_M^{R^*} = \frac{(1+\mu k)^2}{4(2(1-k)-(1+k)\lambda^2)} - (1+k)\tau$ and $\pi_P^{R^*} = \frac{(1+\mu k)^2}{8(2(1-k)-(1+k)\lambda^2)^2} + (1+k)\tau$.

Lemma 2 demonstrates that the optimal decision is not entirely uniformly affected by both λ, μ and k. Specifically, $\frac{\partial x^{R^*}}{\partial \lambda} > 0$, $\frac{\partial x^{R^*}}{\partial \mu} > 0$, $\frac{\partial x^{R^*}}{\partial k} > 0$, where $x \in \{r, q\}$, while $\frac{\partial w^{R^*}}{\partial \lambda} > 0$ and $\frac{\partial w^{R^*}}{\partial \mu} > 0$. Notably, w^{R^*} is not affected by λ if the brand manufacturer adopts the *R*-strategy. This highlights that the brand manufacturer can increase marginal revenue by requesting that the streamer improve their live-streaming service quality and expand their influence among consumers.

Proposition 2. *Under the R-Strategy, we have* $\frac{\partial \pi_i^{R^*}}{\partial \lambda} > 0$ *and* $\frac{\partial \pi_i^{R^*}}{\partial \mu} > 0$ $(i = M, P)$.

Proposition 2 shows that the participant's profit is consistently affected by λ and μ under the *R*-Strategy, i.e., both the manufacturer's and the streamer's profits increase with increasing λ and μ, respectively. Thus, participants in live-streaming e-commerce can increase their profits by improving consumer's sensitivity to service quality or expanding the streamer's influence among consumers.

4.3. Streamer-Led Strategy (L-Strategy)

In the live-stream selling service system, if the streamer is the leader and the brand manufacturer is the follower, it also forms a Stackelberg game. Here, the streamer first decides the commission and the live-streaming service quality to maximize their profits. Then, the brand manufacturer determines the marginal revenue of the product based on the commission and the live-streaming service quality set by the streamer to maximize their profits. This lemma can be obtained using the inverse method.

Lemma 3. *Under the L-Strategy, (i) the optimal decision of the brand manufacturer is* $w^{L^*} = \frac{1+\mu k}{4(1-k)-(1+k)\lambda^2}$*, and (ii) the optimal decisions of the streamer are* $r^{L^*} = \frac{2(1+\mu k)}{4(1-k)-(1+k)\lambda^2}$ *and* $q^{L^*} = \frac{\lambda(1+k)(1+\mu k)}{4(1-k)-(1+k)\lambda^2}$.

Substituting the above results into (1) and (2), we obtain the optimal profits obtained by the brand manufacturer and the streamer as follows: $\pi_M^{L^*} = \frac{(1-k)(1+\mu k)^2}{(4(1-k)-(1+k)\lambda^2)^2} - (1+k)\tau$ and $\pi_P^{L^*} = \frac{(1+\mu k)^2}{8(1-k)-2(1+k)\lambda^2} + (1+k)\tau$.

Lemma 3 shows that the optimal decisions are uniformly affected by λ, μ and k if the brand manufacturer takes the *L*-Strategy in live-stream selling service systems, i.e., $\frac{\partial x^{L^*}}{\partial \lambda} > 0$, $\frac{\partial x^{L^*}}{\partial \mu} > 0$, $\frac{\partial x^{L^*}}{\partial k} > 0$, where $x \in \{w, r, q\}$. Thus, the brand manufacturer and the streamer can reduce consumers' price sensitivity by increasing the streamer's influence among consumers or improving the live-streaming service quality. Moreover, they can also enhance consumers' receptiveness to the streamer's live-streaming sales service.

Proposition 3. *Under the L-Strategy, we have* $\frac{\partial \pi_i^{L^*}}{\partial \lambda} > \mathbf{0}$ $\frac{\partial \pi_i^{L^*}}{\partial \mu} > \mathbf{0}, (\boldsymbol{i} = \boldsymbol{M}, \boldsymbol{P})$.

Proposition 3 indicates the impact of $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$ on participants' profits under the *L*-Strategy. We find that their profits increase with increasing $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$. Thus, if the manufacturer adopts the *L*-Strategy, they can increase their profits by improving the consumer's sensitivity to the streamer's service quality and expanding the streamer's influence among consumers.

5. Comparative Analysis

5.1. The Impact of λ on the Manufacturer's Strategy

In this section, we analyze the influence of consumer sensitivity $\boldsymbol{\lambda}$ on the brand manufacturer's cooperation strategy. By comparing the brand manufacturer's marginal revenue, the streamer's commission and service quality, and their related profits, we draw the following findings.

Proposition 4. *Under different cooperation strategies, the consumer's demand satisfies: (i)* $\boldsymbol{d}^{\boldsymbol{L}^*} < \boldsymbol{d}^{\boldsymbol{R}^*} < \boldsymbol{d}^{\boldsymbol{N}^*}$ *if* $\mathbf{0} < \boldsymbol{\lambda} < \sqrt{\frac{\mathbf{1}-\boldsymbol{k}}{\mathbf{1}+\boldsymbol{k}}}$*, and (ii)* $\boldsymbol{d}^{\boldsymbol{L}^*} < \boldsymbol{d}^{\boldsymbol{N}^*} < \boldsymbol{d}^{\boldsymbol{R}^*}$ *if* $\sqrt{\frac{\mathbf{1}-\boldsymbol{k}}{\mathbf{1}+\boldsymbol{k}}} \le \boldsymbol{\lambda} < \sqrt{\frac{\mathbf{2}(\mathbf{1}-\boldsymbol{k})}{\mathbf{1}+\boldsymbol{k}}}$.

Proposition 4 shows that the streamer's role (for a fixed $\boldsymbol{k}$) in live sales strongly influences the consumer's willingness to buy. That is, the consumer's demand depends on their sensitivity to the streamer's service quality. The manufacturer makes the most extra money by picking the *N*-Strategy and the least by picking the *R*-Strategy if $\mathbf{0} < \boldsymbol{\lambda} < \sqrt{\frac{\mathbf{1}-\boldsymbol{k}}{\mathbf{1}+\boldsymbol{k}}}$. Meanwhile, the manufacturer makes the most extra money by using the *R*-Strategy if $\sqrt{\frac{\mathbf{1}-\boldsymbol{k}}{\mathbf{1}+\boldsymbol{k}}} \le \boldsymbol{\lambda} < \sqrt{\frac{\mathbf{2}(\mathbf{1}-\boldsymbol{k})}{\mathbf{1}+\boldsymbol{k}}}$; see Figure 2 ($\boldsymbol{k} = \mathbf{0.5}, \boldsymbol{\mu} = \mathbf{0.3}$). We find that no single strategy is best in every situation, the manufacturer earns the least extra money with the *L*-Strategy. Therefore, the brand manufacturer adopts the cooperation strategy according to the consumer's sensitivity to the streamer's service quality.

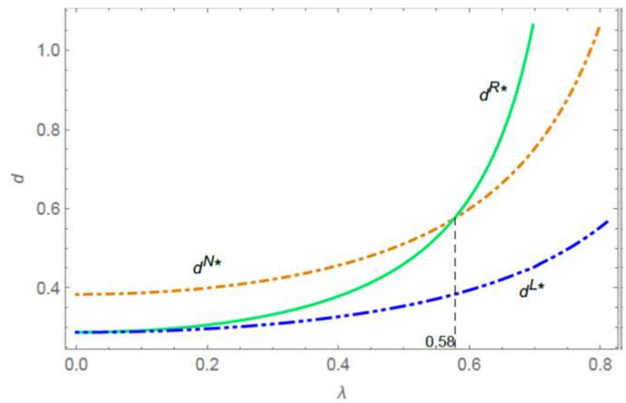


Figure 2. The impact of λ on d under different strategies.

Proposition 5. *Under different cooperation strategies, the manufacturer's marginal revenue satisfies: (i)* $\boldsymbol{w}^{\boldsymbol{L}^*} < \boldsymbol{w}^{\boldsymbol{N}^*} < \boldsymbol{w}^{\boldsymbol{R}^*}$ *when* $\mathbf{0} < \boldsymbol{\lambda} < \sqrt{\frac{\mathbf{1}-\boldsymbol{k}}{\mathbf{1}+\boldsymbol{k}}}$*; (ii)* $\boldsymbol{w}^{\boldsymbol{L}^*} < \boldsymbol{w}^{\boldsymbol{R}^*} \le \boldsymbol{w}^{\boldsymbol{N}^*}$ *when* $\sqrt{\frac{\mathbf{1}-\boldsymbol{k}}{\mathbf{1}+\boldsymbol{k}}} \le \boldsymbol{\lambda} < \sqrt{\frac{\mathbf{2}(\mathbf{1}-\boldsymbol{k})}{\mathbf{1}+\boldsymbol{k}}}$.

Proposition 5 demonstrates that streamer status plays a pivotal role in determining the manufacturer's marginal revenue. The optimal streamer strategy varies with the level of consumer sensitivity $\boldsymbol{\lambda}$. Collaborating with a regular streamer (*R*-Strategy) generates the highest marginal revenue if $\mathbf{0} < \boldsymbol{\lambda} < \sqrt{\frac{\mathbf{1}-\boldsymbol{k}}{\mathbf{1}+\boldsymbol{k}}}$, whereas partnering with a lead streamer (*L*-Strategy) yields the lowest. As consumer sensitivity increases to $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, the N-Strategy becomes the most profitable alternative, as illustrated in Figure 3 ($k = 0.5, \mu = 0.3,$ which deduce the threshold value $\lambda = 0.577$). These results indicate that no single streamer strategy is universally optimal, while the consistently weaker performance of the *L*-Strategy can be attributed to the substantial bargaining power of lead streamers.

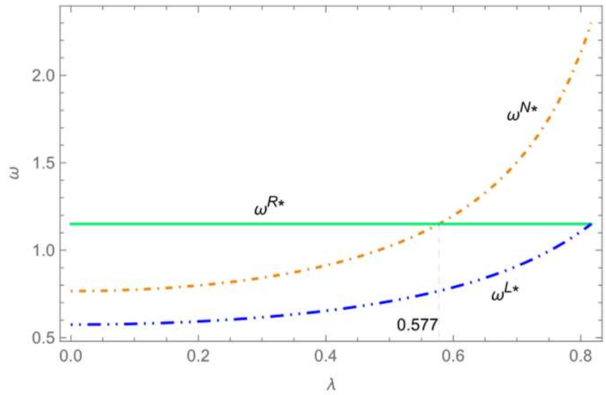


Figure 3. The impact of λ on w under different strategies.

Proposition 6. *Under different cooperation strategies, the streamer's commission satisfies: (i)* $r^{R^*} < r^{N^*} < r^{L^*}$ *if* $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$*; (ii)* $r^{N^*} < r^{R^*} < r^{L^*}$ *if* $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{4(1-k)}{3(1+k)}}$*; and (iii)* $r^{N^*} < r^{L^*} < r^{R^*}$ *if* $\sqrt{\frac{4(1-k)}{3(1+k)}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$.

Proposition 6 reveals that a streamer's status plays a decisive role in determining commission earnings under different market conditions. Specifically, the streamer's commission depends jointly on consumers' sensitivity to service quality and the streamer's market influence. When $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, a dominant streamer operating in the leadership position secures the highest commission, whereas a streamer in the follower position receives the lowest. As consumer's sensitivity increases to $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{4(1-k)}{3(1+k)}}$, the dominant streamer continues to earn the highest commission, while the Nash bargaining arrangement becomes the least favorable for the streamer. When $\sqrt{\frac{4(1-k)}{3(1+k)}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, the follower position becomes the most advantageous for the streamer, whereas the newcomer strategy (*N*-Strategy) generates the lowest commission, as illustrated in Figure 4 ($k = 0.5, \mu = 0.3$), which deduce the threshold values $\lambda_0 = 0.577$ and $\lambda_1 = 0.667$). These findings suggest that the commission-maximizing governance structure shifts systematically with the consumer's responsiveness to service quality.

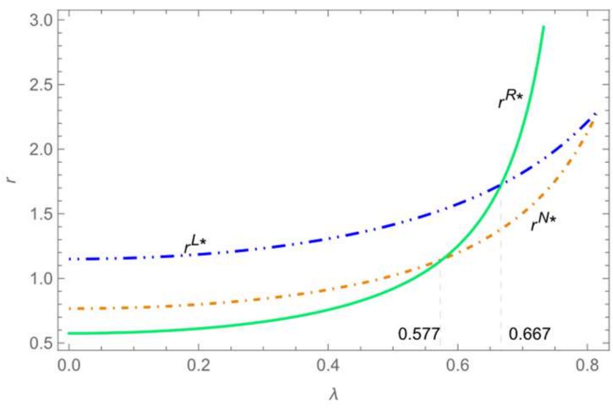


Figure 4. The impact of λ on r under different strategies.

Proposition 7. *Under different cooperation strategies, the streamer's service quality in live-stream selling satisfies: (i)* $q^{L*} < q^{R*} < q^{N*}$ *when* $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$*; (ii)* $q^{L*} < q^{N*} \le q^{R*}$ *when* $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$.

Proposition 7 demonstrates that the streamer's optimal service quality is jointly determined by consumers' sensitivity to service quality and the streamer's market influence. The newcomer strategy (*N*-Strategy) induces the highest level of service quality if $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, whereas the lead streamer strategy (*L*-Strategy) results in the lowest. As consumer sensitivity increases to $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, streamers collaborating under the regular streamer strategy (*R*-Strategy) are incentivized to provide the highest service quality, while the *L*-Strategy continues to require only a relatively low level of service quality, as illustrated in Figure 5 ($k = 0.5, \mu = 0.3$). This result reflects a substitution effect between market influence and service effort, while the lowest service quality consistently arises when a dominant streamer is employed under the *L*-Strategy across all market conditions.

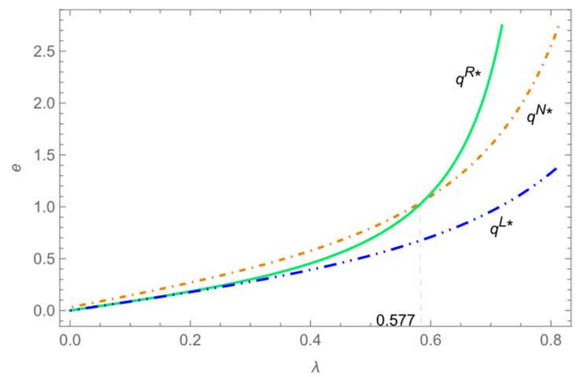


Figure 5. The impact of λ on q under different strategies.

Proposition 8. *Under different cooperation strategies, the brand manufacturer's profit satisfies:* $\pi_M^{L*} < \pi_M^{N*} < \pi_M^{R*}$.

Proposition 8 shows that the allocation of channel leadership has a significant impact on the brand manufacturer's profitability. The manufacturer achieves the highest profit when it assumes the leadership role in the live-stream selling system, followed by the Nash strategy (*N*-Strategy), while the lowest profit is obtained when a dominant streamer leads the channel, as illustrated in Figure 6 ($k = 0.5, \mu = 0.3$). Therefore, it is critical that the manufacturer strategically selects a suitable streamer based on their specific circumstances and brand strategy to maximize income and sustain long-term profitability.

Proposition 9. *For different cooperation strategies, the streamer's profit satisfies: (i)* $\pi_P^{R*} < \pi_P^{N*} < \pi_P^{L*}$ *when* $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$*; (ii)* $\pi_P^{N*} \le \pi_P^{R*} < \pi_P^{L*}$ *when* $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{4(1-k)}{3(1+k)}}$*; and (iii)* $\pi_P^{N*} < \pi_P^{L*} \le \pi_P^{R*}$ *when* $\sqrt{\frac{4(1-k)}{3(1+k)}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$.

Proposition 9 demonstrates that a streamer's profit is strongly influenced by both the channel governance structure and consumers' sensitivity to service quality. The streamer achieves the highest profit by occupying the leadership position if $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, whereas the follower position generates the lowest return. As consumer sensitivity increases to $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{4(1-k)}{3(1+k)}}$, the leadership position remains the most profitable, while the newcomer strategy (N-Strategy) produces the lowest streamer profit. When $\sqrt{\frac{4(1-k)}{3(1+k)}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, the profit ranking changes again, indicating that the streamer's optimal governance position depends critically on the consumer's responsiveness to service quality, as illustrated in Figure 7 ($k = 0.5, \mu = 0.3, \tau = 0.2$). This result reflects that improvement in service quality increases consumer engagement and purchasing intentions, thereby enhancing the streamer's bargaining position within the channel.

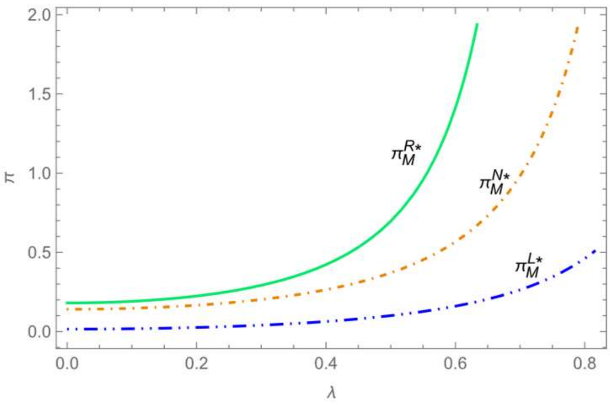


Figure 6. The impact of λ on π_M^j under different strategies.

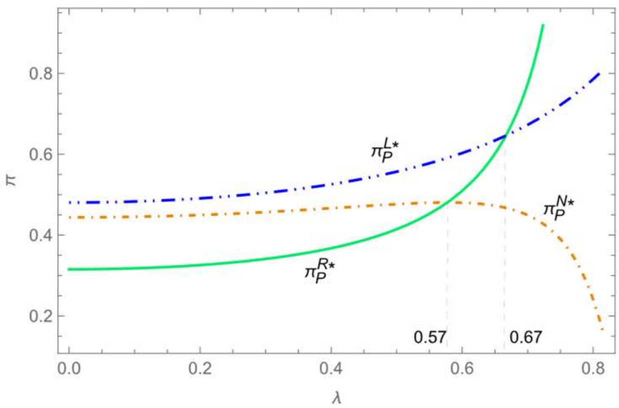


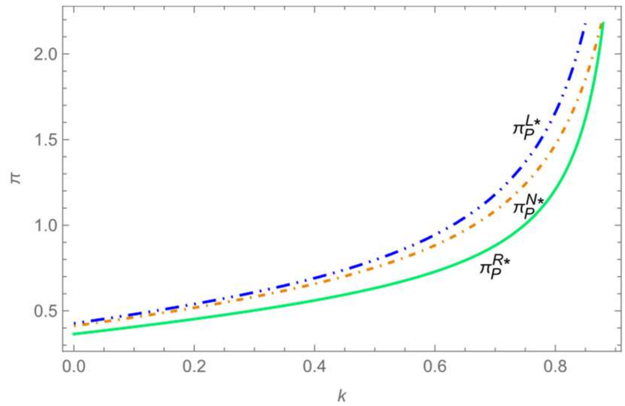
Figure 7. The impact of λ on π_P^j under different strategies.

Figures 6 and 7 further illustrate that the optimal collaboration strategy depends on the strategic alignment between manufacturer and streamer characteristics rather than on streamer popularity alone. Under certain market conditions, partnering with a less influential streamer can be more profitable for the manufacturer because it preserves greater control over pricing, channel operations, and profit allocation throughout the live-streaming process. When consumers exhibit relatively low sensitivity to service quality ($\lambda \leq 0.667 = \sqrt{\frac{4(1-0.5)}{3(1+0.5)}}$), or when streamers possess a strong and loyal follower base, streamers capture a larger share of the economic value generated through live-streaming commerce. By contrast, streamers with relatively limited market influence have stronger incentives to collaborate with well-established manufacturers in order to enhance product credibility, expand audience reach, and improve commercial performance.

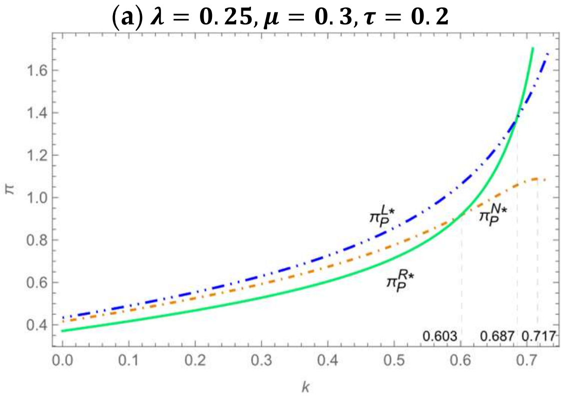
5.2. The Impact of k on the Brand Manufacturer's Strategy

This section investigates how streamer charisma (k) influences the manufacturer's cooperation strategy and the profit distribution between manufacturers and streamers. Streamer charisma reflects consumers' perceptions of a streamer's attractiveness and persuasive ability, which directly affect consumer purchasing behavior and the strategic interaction between manufacturers and streamers. To isolate the effect of charisma, we fix $\mu = 0.3, \tau = 0.2$, and impose the condition $k < \frac{2-\lambda^2}{2+\lambda^2}$.

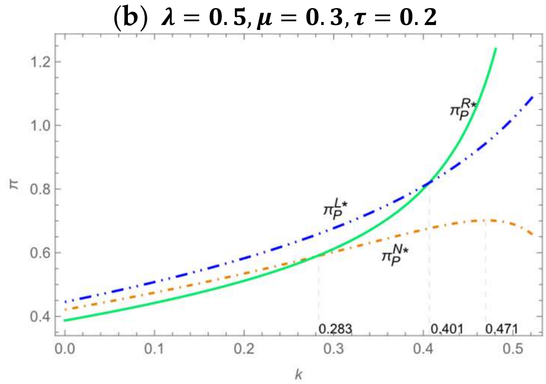
Figure 8a–c illustrates the effect of streamer charisma on streamer profit under different cooperation strategies for three levels of consumer sensitivity to service quality ($\boldsymbol{\lambda} = \mathbf{0.20}$, $\mathbf{0.50}$, and $\mathbf{0.75}$). When consumer sensitivity is relatively low ($\boldsymbol{\lambda} = \mathbf{0.25}$), the streamer's profit increases monotonically with charisma across all cooperation strategies, with the strongest positive effect observed when the manufacturer retains channel leadership (Figure 9a). However, as consumer sensitivity increases ($\boldsymbol{\lambda} = \mathbf{0.50}$ and $\mathbf{0.75}$), the relationship becomes nonlinear under the Nash strategy (*N*-Strategy). Specifically, the streamer's profit first increases and then decreases with charisma, yielding threshold values of $\boldsymbol{k_0} = \mathbf{0.717}$ and $\boldsymbol{k_0} = \mathbf{0.471}$, respectively (Figure 9b,c). This finding suggests that excessive charisma does not always improve streamer profitability. Beyond the threshold, the additional bargaining power associated with higher charisma raises commission expectations and intensifies channel conflicts, thereby reducing the streamer's net earnings.



(a) $\boldsymbol{\lambda = 0.25, \mu = 0.3, \tau = 0.2}$

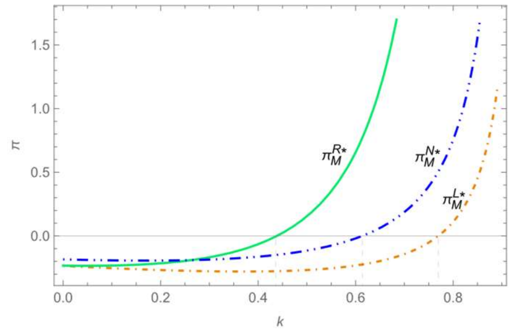


(b) $\boldsymbol{\lambda = 0.5, \mu = 0.3, \tau = 0.2}$

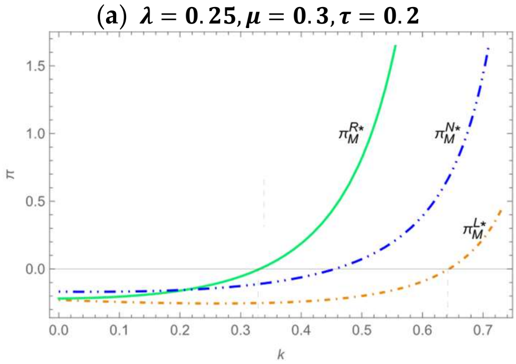


(c) $\boldsymbol{\lambda = 0.75, \mu = 0.3, \tau = 0.2}$

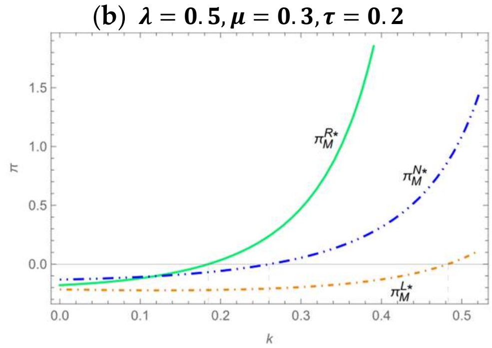
Figure 8. The impact of $\boldsymbol{k}$ on $\boldsymbol{\pi_P^j}$ under different strategies.



(a) $\lambda = 0.25, \mu = 0.3, \tau = 0.2$



(b) $\lambda = 0.5, \mu = 0.3, \tau = 0.2$



(c) $\lambda = 0.75, \mu = 0.3, \tau = 0.2$

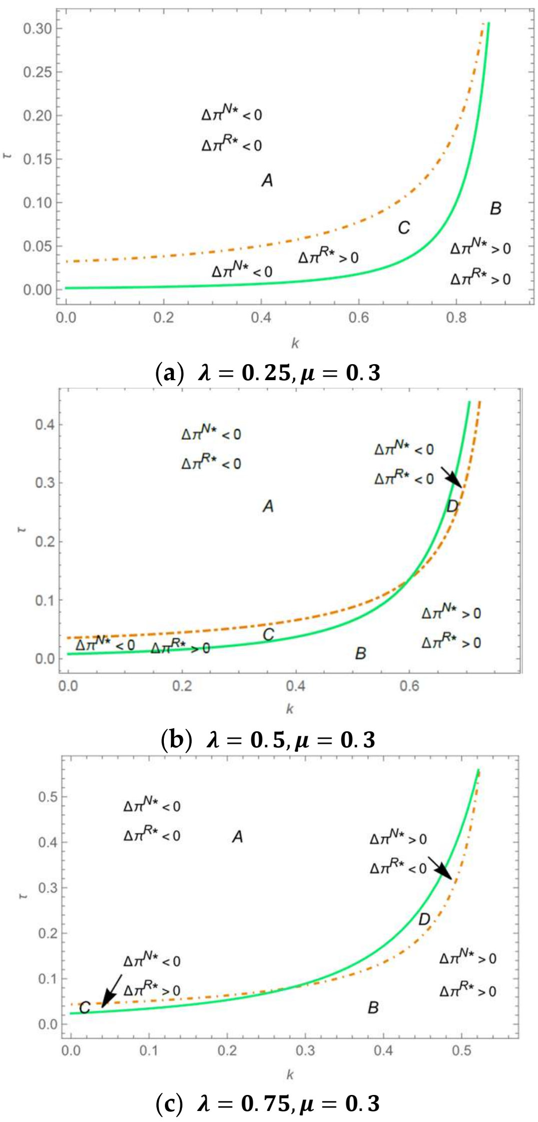
Figure 9. The impact of k on π_M^j under different strategies.

Another notable observation is that streamer charisma has the greatest positive effect on streamer profit when the manufacturer leads the live-stream channel. Under manufacturer leadership, highly charismatic streamers can leverage their influence to attract consumers while maintaining an efficient collaboration with the manufacturer. Consequently, streamers should continuously strengthen their professional capabilities, personal branding, and consumer engagement to enhance the commercial value of live-streaming.

5.3. Revenue Gaps

In this section, we will analyze the impact of two key parameters, namely, the streamer's fixed link fee τ and their charisma as perceived by consumers k, on the revenue gaps of the participants in the live-stream selling service system. Thus, we have $\Delta\pi^{N*} = \frac{1+k}{2}\left(\frac{\lambda^2(1+\mu k)^2}{(3(1-k)-(1+k)\lambda^2)^2} - 4\tau\right)$, where $\Delta\pi^{j*} = \pi_M^{j*} - \pi_P^{j*} (j = N, R, L)$ denote the profit gaps in the j-Strategy scenario. The manufacturer's live-stream selling revenue is dominant when $\tau < \frac{\lambda^2(1+\mu k)^2}{4(3(1-k)-(1+k)\lambda^2)^2}$. If the streamer's fixed link fee τ is lower, the manufacturer can get more revenue than the streamer in the N-Strategy. Similarly, we also have $\Delta\pi^{R*} = \frac{(1+\mu k)^2}{8(2(1-k)-(1+k)\lambda^2)} - 2(1+k)\tau$, and $\Delta\pi^{L*} = -\frac{(2(1-k)-(1+k)\lambda^2)(1+\mu k)^2}{2(4(1-k)-(1+k)\lambda^2)^2} - 2(1+k)\tau$. We find that the manufacturer always gets less revenue than that of the streamer if they adopt the L-strategy in the live-streaming service system, while the brand manufacturer's live-stream selling revenue can get more revenue than that of the streamer if $\tau < \frac{(1+\mu k)^2}{16(1+k)(2(1-k)-(1+k)\lambda^2)^2}$. Without loss of generality, the parameters are set as follows: $\mu = 0.3$, $\lambda = 0.25, 0.5, 0.75$, and $k < \frac{2-\lambda^2}{2+\lambda^2}$; the results are presented in Figure 9a–c, corresponding to $\lambda = 0.25$, $\lambda = 0.5$, and $\lambda = 0.75$, respectively.

Figure 10a–c show that the manufacturer's revenue does not need to be dominant over the streamer's in either the *N*-Strategy or *R*-Strategy scenario. The manufacturer's revenue is higher than the streamer's when the streamer's fixed link fee, τ, and their charisma as perceived by consumers, *k*, fall within zone ***B***. In comparison, the streamer's revenue is higher than that of the manufacturer within zone ***A***. In zones ***C*** and ***D***, the participant's revenue in the live-stream selling service system is not affected by the other player's *N*-Strategy or *R*-Strategy. In summary, the manufacturer can achieve dominant revenue in a live-streaming service system if the streamer has high charisma and requires a low fixed link fee. Meanwhile, the streamer can generate dominant revenue if they ask for a high fixed link fee with modest charisma. For a streamer with low influence and a low fixed link fee, or with high charisma and a high fixed link fee, the brand manufacturer can adopt a suitable cooperative strategy within a live-streaming service system to generate considerable revenue.



(a) $\lambda = 0.25, \mu = 0.3$

(b) $\lambda = 0.5, \mu = 0.3$

(c) $\lambda = 0.75, \mu = 0.3$

Figure 10. The impact of τ and k on the revenue gaps.

6. Illustrative Case Study

The purpose of this section is not to empirically estimate the proposed game-theoretical model but rather to examine whether the observed cooperation patterns on the Douyin platform are broadly consistent with the model's theoretical predictions.

Two representative cosmetic brands are examined: PerfectDiary (P-brand), a Chinese beauty company established in 2016 that emphasizes contemporary fashion and user-friendly makeup, and Estée Lauder (E-brand), founded in 1946, which offers a broad portfolio of cosmetics, perfumes, and skincare products for both women and men. P-brand initiated collaboration with Douyin in February 2018 to enhance e-commerce live-streaming, whereas E-brand commenced its live-streaming activities in early 2020 during the COVID-19 outbreak.

KOL streamers' live-streams are selected and promoted using a mixed strategy that combines a few star hosts with a larger number of mid-to-high-level vertical streamers to more comprehensively reach the target demographic of 18–23-year-old female users. For live-streaming sales, P-brand selects the best-selling items from the previous 30 days, including lipstick, highlighter/contour, eyeshadow, and makeup remover. The live-streaming sales data for P-brand and E-brand beauty series are collected from 19 November 2024 to 25 November 2024 on the Douyin (TikTok) platform (https://dy.huitun.com/app/#/dashboard, accessed on 19 November 2024 and 25 November 2024). These data include the streamer's accumulative fan count, session count, sales volume, and total sales volume, as detailed in Table 2. However, several parameters remain unavailable, such as live-streaming stimulus, commission and the fixed link fee.

Table 2. An overview of P-brand and E-brand on the Douyin live-streaming platform.

Brand	Streamer's ID	Accumulative Fan Count	Sessions	Average Sales	Total Sales
PerfectDiary	PerfectDiary01	6516.5	6	75–100	250–500
	PerfectDiaryTop	1879.6	12	10–25	100–250
	pd-xxx	1047.1	14	2.5–5	10–25
	PerfectDiaryMZ	523	6	7.5–5	25–50
	PerfectDiary19	233.1	4	25–50	10–25
	WM.live	93.5	8	7.5–10	50–75
EsteeLauder	628xxx	6536	7	100–250	500–750
	naisgmg	2246	3	100–250	250–500
	duoduo2016aa	921	3	75–100	500–750
	533xxx	247	9	25–50	100–250
	442xxx	195	7	10–25	50–75

Source: https://dy.huitun.com/app/#/app/anchor/anchor_list from 19 November 2024 to 25 November 2024, accessed on 19 November 2024 and 25 November 2024.

The analysis reveals that, across all streamer tiers, well-known brands consistently outperform lesser-known brands in both sales volumes and session totals. For P-brand manufacturers, collaborating with top-tier streamers yields higher total sales and session volumes. For instance, PerfectDiary01 drives sales ranging from 41,670 to 83,300 CNY with 12.5 to 16.7 items per session, whereas general-level streamers like PerfectDiary19 see significantly lower results. Despite some variability, per capita contribution rates and fan purchasing rates remain generally low. For E-brand manufacturers, partnerships with top-level streamers lead to significant increases in both sales and sales volume per session. For instance, a streamer with 628,000 fans generated 71,428 to 107,123 CNY and 14.3 to 35.7 items per session. In contrast, general-level streamers with 442,000 fans produced only 7142.8 to 10,714.3 CNY and 1.4 to 3.5 items per session. The per capita contribution rate ranges from 1.1% to 40.7%, and is generally higher with general-level streamers. Fan purchasing rates range from 1.6% to 27.1%.

Based on the above empirical validation, we find that the following: (1) Mid- to low-end manufacturers generate lower revenue per session than medium- to high-end brands, regardless of streamer type. (2) Mid- to low-end manufacturers focus on cost efficiency and tend to partner with ordinary streamers. (3) Medium- to high-end manufacturers see greater returns from working with high-profile streamers. However, this empirical validation offers only preliminary qualitative support, and its findings should be interpreted with caution, as they should not be regarded as strict empirical evidence for the model's predictions. In addition, the empirical data were sourced exclusively from a single platform (Douyin) including two cosmetic brands, and span merely one week, which severely limits sample representativeness and generalizability. Moreover, key model parameters (such as live-streaming stimulus effects and fixed link fees) are unavailable, while core variables like consumer sensitivity, service quality, and commission rates are not directly observable.

7. Discussion and Implications

This study examines how manufacturers should design cooperation strategies with streamers in live-streaming commerce by considering the joint effects of streamer status and consumer sensitivity to service quality. Through a combination of game-theoretic modeling and corroborative analysis based on Douyin (TikTok) live-stream sales data, the study identifies the optimal governance structures under different market conditions and explains how pricing, service quality, commission allocation, and profit distribution evolve across alternative cooperation modes. These findings enrich the literature on channel governance and platform-based commerce while providing actionable guidance for manufacturers in selecting appropriate live-stream partners.

7.1. Theoretical Contributions

This study advances the live-stream commerce literature by explicitly endogenizing the cooperation structure between manufacturers and streamers. Unlike prior studies that primarily examine firms' live-stream adoption decisions (e.g., [19,20]) or contract design under exogenously given governance structures (e.g., [46,47]), we treat channel governance as a strategic decision variable. By comparing manufacturer-led, streamer-led, and Nash bargaining cooperation structures within a unified game-theoretic framework, we demonstrate how alternative governance arrangements systematically reshape pricing decisions, service quality provision, commission allocation, and profit distribution.

A second theoretical contribution lies in uncovering the nonlinear role of streamer influence. Our analysis shows that greater influence may reduce incentives to invest in service quality because dominant streamers increasingly rely on their market power rather than service effort. This substitution effect between market influence and service investment reveals an overlooked incentive distortion in live-stream commerce. It enriches the information-processing literature by showing that the value of live-stream information depends jointly on information credibility, governance mechanisms, and incentive alignment.

Third, this study identifies threshold effects associated with consumers' sensitivity to service quality. Rather than assume that improvements in service quality uniformly increase firm performance, we show that consumer responsiveness fundamentally alters the relative efficiency of alternative cooperation structures. Consequently, the optimal governance arrangement is contingent on both consumer behavior and streamer characteristics.

Finally, by integrating analytical modeling with empirical evidence from the Douyin (TikTok) platform, this study bridges the gap between formal decision models and real-world live-stream commerce practices. The empirical results provide empirical support for the proposed theoretical framework and demonstrate its practical relevance in explaining observed cooperation patterns across different types of streamers.

7.2. Managerial Implications

The findings of this study provide several important managerial implications for manufacturers, streamers, and platform operators. For manufacturers, the results indicate that collaborating with the most influential streamer does not necessarily maximize profitability. Although top-tier streamers can substantially expand consumer demand, their stronger bargaining power and higher commission requirements often offset these benefits. Manufacturers should therefore design cooperation strategies by jointly considering streamer influence and consumer sensitivity to service quality, rather than relying solely on follower size or market popularity.

For streamers, the results suggest that sustainable competitive advantage depends not only on market influence but also on continued investment in service quality. As streamer influence increases, the incentive to improve service quality may weaken because market power increasingly substitutes for service effort. However, this strategy may ultimately reduce long-term cooperation opportunities and channel efficiency. Streamers should therefore strengthen consumer engagement through professional product presentation, interactive communication, and improved service quality instead of relying solely on accumulated popularity.

7.3. Limitations and Future Research

Despite this study's contributions, several limitations provide opportunities for future research. First, the present study models streamer influence as an exogenous characteristic. Future research could endogenize reputation formation by incorporating dynamic learning or repeated interactions. Second, the study captures consumer heterogeneity primarily through sensitivity to service quality. Extending the framework to include heterogeneous preferences for price, brand reputation, trust, or social influence would further strengthen the model's behavioral foundations. Finally, integrating emerging technologies such as AI-generated streamers, generative AI-assisted live-streaming, and algorithmic recommendation systems into the analytical framework would provide valuable insights into the future evolution of platform-based live-stream commerce.

Author Contributions: Conceptualization, M.C.; methodology, M.C.; software, Y.C.; validation, Y.C. and X.L.; formal analysis, M.C., X.S. and Y.C.; investigation, X.S.; resources, Y.C.; data curation, Y.C.; writing—original draft preparation, X.S.; writing—review and editing, X.S., Y.C. and X.L.; supervision, M.C.; project administration, X.L.; funding acquisition, M.C. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Proof of Lemma 1. Taking the first-order partial derivatives of π_M^N and π_P^N with respect to w, r and q, respectively, we have

$$\frac{\partial \pi_M^N}{\partial w} = 1 + \lambda q + \mu k - 2(1-k)w - (1-k)r \tag{A1}$$

$$\frac{\partial \pi_P^N}{\partial r} = 1 + \lambda q + \mu k - 2(1-k)r - (1-k)w \tag{A2}$$

$$\frac{\partial \pi_P^N}{\partial q} = r\lambda - \frac{q}{1+k} \tag{A3}$$

From $\frac{\partial^2 \pi_M^N}{\partial w^2} = -2(1-k) < 0$, and $\frac{\partial^2 \pi_P^N}{\partial r^2} = -2(1-k) < 0$, $\frac{\partial^2 \pi_P^N}{\partial r \partial q} = \lambda$ and $\frac{\partial^2 \pi_P^N}{\partial q^2} = -\frac{1}{1+k} < 0$, it is determined that π_M^N is a concave function with respect to w, and π_P^N is a joint concave function with respect to r and q under the condition of $0 < \lambda < \sqrt{\frac{2(1-k)}{1+k}}$. That is, π_M^N and π_P^N represent unique optimal decisions about w and r, q, respectively.

By solving $\frac{\partial \pi_M^N}{\partial w} = 0$, $\frac{\partial \pi_P^N}{\partial r} = 0$ and $\frac{\partial \pi_P^N}{\partial q} = 0$, the optimal decisions are given as follows: $w^{N*} = \frac{1+\mu k}{3(1-k)-(1+k)\lambda^2}$, $r^{N*} = \frac{1+\mu k}{3(1-k)-(1+k)\lambda^2}$ and $q^{N*} = \frac{\lambda(1+k)(1+\mu k)}{3(1-k)-(1+k)\lambda^2}$. □

Proof of Proposition 1.

(i) Taking the first-order partial derivative of π_M^{N*} with respect to λ, we have $\frac{\partial \pi_M^{N*}}{\partial \lambda} = \frac{4\lambda\left(1-k^2\right)(1+\mu k)^2}{\left(3(1-k)-(1+k)\lambda^2\right)^3} > 0$.

(ii) For π_P^{N*}, we also have $\frac{\partial \pi_P^{N*}}{\partial \lambda} = \frac{\lambda(1+k)((1-k)-(1+k)\lambda^2)(1+\mu k)^2}{\left(3(1-k)-(1+k)\lambda^2\right)^3}$. Since $0 < \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, we determine that $\frac{\partial \pi_P^{N*}}{\partial \lambda} > 0$ if $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, and $\frac{\partial \pi_P^{N*}}{\partial \lambda} \leq 0$ if $\sqrt{\frac{1-k}{1+k}} \leq \lambda < \sqrt{\frac{2(1-k)}{1+k}}$.

(iii) Taking the first-order partial derivative of $\pi_i^{N*} (i = M, P)$ with respect to μ, respectively, we have $\frac{\partial \pi_M^{N*}}{\partial \mu} = \frac{2k(1-k)(1+\mu k)}{\left(3(1-k)-(1+k)\lambda^2\right)^3} > 0$ and $\frac{\partial \pi_P^{N*}}{\partial \mu} = \frac{k(2(1-k)-(1+k)\lambda^2)(1+\mu k)}{\left(3(1-k)-(1+k)\lambda^2\right)^2} > 0$.

□

Proof of Lemma 2. Taking the first-order partial derivative of π_P^R with respect to r and q, respectively, we have

$$\frac{\partial \pi_P^R}{\partial r} = 1 - 2(1-k)r + \lambda q + \mu k - (1-k)w \tag{A4}$$

$$\frac{\partial \pi_P^R}{\partial q} = \lambda r - \frac{q}{1+k} \tag{A5}$$

From Equations (A4) and (A5), the Hessian matrix of π_P^R with respect to r and q can be obtained:

$$H\left(\pi_P^R\right) = \begin{bmatrix} \frac{\partial^2 \pi_P^R}{\partial r^2} & \frac{\partial^2 \pi_P^R}{\partial r \partial q} \\ \frac{\partial^2 \pi_P^R}{\partial q \partial r} & \frac{\partial^2 \pi_P^R}{\partial q^2} \end{bmatrix} = \begin{bmatrix} -2(1-k) & \lambda \\ \lambda & -\frac{1}{1+k} \end{bmatrix}$$

It is easy to verify that π_P^R is a joint concave function with respect to r and q. Thus, π_P^R has a unique equilibrium with respect to r and q under the condition $0 < \lambda < \sqrt{\frac{2(1-k)}{1+k}}$. By solving equations $\frac{\partial \pi_P^R}{\partial r} = 0$ and $\frac{\partial \pi_P^R}{\partial q} = 0$, we have

$$r^{R*} = \frac{1 + \mu k - w + kw}{2(1-k) - (1+k)\lambda^2} \text{ and } q^{R*} = \frac{\lambda(1+k)(1 + \mu k - w + kw)}{2(1-k) - (1+k)\lambda^2} \tag{A6}$$

Substituting r^{R*} and q^{R*} into π_M^R and taking the first- and second-order partial derivatives of $\pi_{\mathbf{M}}^{\mathbf{R}}$ with respect to w, we have $\frac{\partial \pi_M^R}{\partial w} = \frac{(1-k)(1+\mu k) - 2(1-k)^2 w}{2(1-k)-(1+k)\lambda^2}$ and $\frac{\partial^2 \pi_M^R}{\partial w^2} = \frac{-2(1-k)^2}{2(1-k)-(1+k)\lambda^2} < 0$, that is, π_M^R is a concave function with respect to w.

By solving $\frac{\partial \pi_M^R}{\partial w} = 0$, we get $w^{R*} = \frac{1+\mu k}{2(1-k)}$. Substituting w^{R*} into Equation (A6), we have $r^{R*} = \frac{1+\mu k}{2(2(1-k)-(1+k)\lambda^2)}$, $q^{R*} = \frac{\lambda(1+k)(1+\mu k)}{2(2(1-k)-(1+k)\lambda^2)}$. □

Proof of Proposition 2. Taking the first-order partial derivative of $\pi_i^R (i = M, P)$ with respect to λ, respectively, we have $\frac{\partial \pi_M^{R*}}{\partial \lambda} = \frac{\lambda(1+k)(1+\mu k)}{2(2(1-k)-(1+k)\lambda^2)^2} > 0$ and $\frac{\partial \pi_P^{R*}}{\partial \lambda} = \frac{\lambda(1+k)(1+\mu k)}{4(2(1-k)-(1+k)\lambda^2)^2} > 0$.

Similarly, we also have $\frac{\partial \pi_M^{R*}}{\partial \mu} = \frac{k(1+\mu k)}{2(2(1-k)-(1+k)\lambda^2)} > 0$ and $\frac{\partial \pi_P^{R*}}{\partial \mu} = \frac{k(1+\mu k)}{4(2(1-k)-(1+k)\lambda^2)} > 0$.
□

Proof of Lemma 3. Taking the first- and second-order partial derivative of π_M^L with respect to w, we have

$$\frac{\partial \pi_M^L}{\partial w} = 1 + \lambda q + \mu k - 2(1-k)w - (1-k)r$$

$$\frac{\partial^2 \pi_M^L}{\partial w^2} = -2(1-k) < 0$$

which means that π_M^L is a concave function with respect to w. Thus, π_M^L has a unique optimal decision with respect to w. By solving $\frac{\partial \pi_M^L}{\partial w} = 0$, we have $w^{L*} = \frac{1-(1-k)r+\lambda q+\mu k}{2(1-k)}$.

Substituting w^{L*} into π_P^L and taking the first-order partial derivative of π_P^L with respect to r and q, respectively, we have

$$\frac{\partial \pi_P^L}{\partial r} = \frac{1}{2}(1 - 2(1-k)r + \lambda q + \mu k) \tag{A7}$$

$$\frac{\partial \pi_P^L}{\partial q} = \frac{1}{2}\lambda r - \frac{q}{1+k} \tag{A8}$$

From Equations (A7) and (A8), the Hessian matrix of π_P^L with respect to r and q can be obtained as follows:

$$H\left(\pi_P^L\right) = \begin{bmatrix} \frac{\partial^2 \pi_P^L}{\partial r^2} & \frac{\partial^2 \pi_P^L}{\partial r \partial q} \\ \frac{\partial^2 \pi_P^L}{\partial q \partial r} & \frac{\partial^2 \pi_P^L}{\partial q^2} \end{bmatrix} = \begin{bmatrix} -(1-k) & \frac{\lambda}{2} \\ \frac{\lambda}{2} & -\frac{1}{1+k} \end{bmatrix}$$

It is easy to verify that π_P^L is a joint concave function with respect to r and q. Thus, π_P^L has a unique equilibrium with respect to r, q under $0 < \lambda < \sqrt{\frac{4(1-k)}{1+k}}$.

By solving $\frac{\partial \pi_P^L}{\partial r} = 0$ and $\frac{\partial \pi_P^L}{\partial q} = 0$, we have $r^{L*} = \frac{2(1+\mu k)}{4(1-k)-(1+k)\lambda^2}$ and $q^{L*} = \frac{\lambda(1+k)(1+\mu k)}{4(1-k)-(1+k)\lambda^2}$. Substituting r^{L*} and q^{L*} into w^{L*}, we have $w^{L*} = \frac{1+\mu k}{4(1-k)-(1+k)\lambda^2}$. □

Proof of Proposition 3. Taking the first-order derivative of $\pi_i^{L*}(i = M, P)$ with respect to λ, respectively, we have $\frac{\partial \pi_M^{L*}}{\partial \lambda} = \frac{4\lambda(1-k^2)(1+\mu k)^2}{(4(1-k)-(1+k)\lambda^2)^3} > 0$, $\frac{\partial \pi_P^{L*}}{\partial \lambda} = \frac{\lambda(1+k)(1+\mu k)^2}{(4(1-k)-(1+k)\lambda^2)^2} > 0$.

Similarly, we also have $\frac{\partial \pi_M^{L*}}{\partial \mu} = \frac{2k(1-k)(1+\mu k)}{(4(1-k)-(1+k)\lambda^2)^2} > 0$, $\frac{\partial \pi_P^{L*}}{\partial \mu} = \frac{k(1+\mu k)}{(4(1-k)-(1+k)\lambda^2)^2} > 0$. □

Proof of Proposition 4. By comparing the consumer's demands under different cooperation strategies, we have

$d^{N*} - d^{L*} = \frac{(1-k)^2(1+\mu k)}{\left(4(1-k)-(1+k)\lambda^2\right)\left(3(1-k)-(1+k)\lambda^2\right)} > 0$, which means that $d^{L*} < d^{N*}$, and $d^{R*} - d^{L*} = \frac{\lambda^2(1-k^2)(1+\mu k)}{2\left(2(1-k)-(1+k)\lambda^2\right)\left(4(1-k)-(1+k)\lambda^2\right)} > 0$, which means that $d^{L*} < d^{R*}$. Thus, $d^{L*} < \min\left\{d^{N*}, d^{R*}\right\}$.

Similarly, $d^{N*} - d^{R*} = \frac{(1-k)((1-k)-(1+k)\lambda^2)(1+\mu k)}{2(2(1-k)-(1+k)\lambda^2)(3(1-k)-(1+k)\lambda^2)}$. It is easy to verify that if $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, we have $d^{R*} < d^{N*}$, and if $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, we have $d^{N*} \le d^{R*}$.

Therefore, we determine that (i) $d^{L*} < d^{R*} < d^{N*}$ when $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, and (ii) $d^{L*} < d^{N*} \le d^{R*}$ when $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$. □

Proof of Proposition 5. Comparing the manufacturer's marginal revenue under different scenarios, we have

$w^{L*} - w^{N*} = -\frac{(1-k)(1+\mu k)}{\left(3(1-k)-(1+k)\lambda^2\right)\left(4(1-k)-(1+k)\lambda^2\right)} < 0$, which means that $w^{L*} < w^{N*}$, and $w^{L*} - w^{R*} = -\frac{(2(1-k)-(1+k)\lambda^2)(1+\mu k)}{2(1-k)\left(4(1-k)-(1+k)\lambda^2\right)}$, which means that $w^{L*} < w^{R*}$. Because $0 < \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, we have $w^{L*} < \min\{w^{R*}, w^{N*}\}$.

Similarly, $w^{N*} - w^{R*} = -\frac{((1-k)-(1+k)\lambda^2)(1+\mu k)}{2(1-k)\left(3(1-k)-(1+k)\lambda^2\right)}$. It is easy to verify that $w^{N*} < w^{R*}$ if $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$ and $w^{R*} \le w^{N*}$ if $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$.

Therefore, we obtain that $w^{L*} < w^{N*} < w^{R*}$ when $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, and $w^{L*} < w^{R*} \le w^{N*}$ when $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$. □

Proof of Proposition 6. Comparing the streamer's commission obtained under different cooperation strategies, we have $r^{N*} - r^{L*} = \frac{\left(2(1-k)-(1+k)\lambda^2\right)(1+\mu k)}{\left(3(1-k)-(1+k)\lambda^2\right)\left(4(1-k)-(1+k)\lambda^2\right)} < 0$, which means that $r^{N*} < r^{L*}$.

Similarly, we also have $r^{R*} - r^{N*} = \frac{((1-k)-(1+k)\lambda^2)(1+\mu k)}{2(2(1-k)-(1+k)\lambda^2)(3(1-k)-(1+k)\lambda^2)}$ and $r^{R*} - r^{L*} = \frac{(4(1-k)-3(1+k)\lambda^2)(1+\mu k)}{2(2(1-k)-(1+k)\lambda^2)(4(1-k)-(1+k)\lambda^2)}$.

Since $0 < \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, it is easy to verify that (i) if $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, then $r^{R*} < r^{N*}$, and (ii) if $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{4(1-k)}{3(1+k)}}$, then $r^{N*} \le r^{R*}$ and $r^{R*} < r^{L*}$, and if $\sqrt{\frac{4(1-k)}{3(1+k)}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, then $r^{L*} < r^{R*}$.

Therefore, we determine that (i) $r^{R*} < r^{N*} < r^{L*}$ when $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$; (ii) $r^{N*} \le r^{R*} < r^{L*}$ when $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{4(1-k)}{3(1+k)}}$; and (iii) $r^{N*} < r^{L*} \le r^{R*}$ when $\sqrt{\frac{4(1-k)}{3(1+k)}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$. □

Proof of Proposition 7. Comparing the streamer's service quality in live-stream selling under different cooperation strategies, we have $q^{N*} - q^{L*} = \frac{\lambda(1-k^2)(1+\mu k)}{(3(1-k)-(1+k)\lambda^2)(4(1-k)-(1+k)\lambda^2)} > 0$ and $q^{R*} - q^{L*} = \frac{\lambda^3(1+k)^2(1+\mu k)}{2(2(1-k)-(1+k)\lambda^2)(4(1-k)-(1+k)\lambda^2)} > 0$, which implies that $q^{L*} < q^{N*}$ and $q^{L*} < q^{R*}$, respectively. Thus, $q^{L*} < \min\{q^{R*}, q^{N*}\}$.

Similarly, $q^{N*} - q^{R*} = \frac{\lambda((1-k)-(1+k)\lambda^2)(1+k)(1+\mu k)}{(2(1-k)-(1+k)\lambda^2)(3(1-k)-(1+k)\lambda^2)}$. Since $0 < \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, we have $q^{R*} < q^{N*}$ if $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, and $q^{N*} \le q^{R*}$ if $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$.

Therefore, we get $q^{L*} < q^{R*} < q^{N*}$ if $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, and $q^{L*} < q^{N*} \le q^{R*}$ if $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$. □

Proof of Proposition 8. By comparing the brand manufacturer's profit under different cooperation strategies, we have $\pi_M^{N*} - \pi_M^{R*} = -\frac{((1-k)-(1+k)\lambda^2)^2(1+\mu k)^2}{4(2(1-k)-(1+k)\lambda^2)(3(1-k)-(1+k)\lambda^2)^2} < 0$, which means that $\pi_M^{N*} < \pi_M^{R*}$.

Similarly, $\pi_M^{L*} - \pi_M^{N*} = -\frac{(1-k)^2(7(1-k)-2(1+k)\lambda^2)(1+\mu k)^2}{(4(1-k)-(1+k)\lambda^2)^2(3(1-k)-(1+k)\lambda^2)^2} < 0$, which means that $\pi_M^{L*} < \pi_M^{N*}$. Thus, $\pi_M^{L*} < \pi_M^{N*} < \pi_M^{R*}$. □

Proof of Proposition 9. By comparing the streamer's profit under different cooperation strategies, we have $\pi_P^{N*} - \pi_P^{L*} = -\frac{(1-k)^2(1+\mu k)^2}{2(3(1-k)-(1+k)\lambda^2)^2(4(1-k)-(1+k)\lambda^2)} < 0$, which means that $\pi_P^{N*} < \pi_P^{L*}$.

Similarly, we also have $\pi_P^{N*} - \pi_P^{R*} = \frac{(7(1-k)-3(1+k)\lambda^2)((1-k)-(1+k)\lambda^2)(1+\mu k)^2}{8(3(1-k)-(1+k)\lambda^2)^2(2(1-k)-(1+k)\lambda^2)}$ and $\pi_P^{R*} - \pi_P^{L*} = -\frac{(4(1-k)-3(1+k)\lambda^2)(1+\mu k)^2}{8(4(1-k)-(1+k)\lambda^2)(2(1-k)-(1+k)\lambda^2)}$.

Obviously, it is easy to verify that (i) if $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$, then $\pi_P^{R*} \le \pi_P^{N*}$; (ii) if $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{4(1-k)}{3(1+k)}}$, then $\pi_P^{N*} \le \pi_P^{R*}$ and $\pi_P^{R*} < \pi_P^{L*}$; and $\sqrt{\frac{4(1-k)}{3(1+k)}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$, then $\pi_P^{L*} \le \pi_P^{R*}$.

Therefore, we get (i) $\pi_P^{R*} < \pi_P^{N*} < \pi_P^{L*}$ when $0 < \lambda < \sqrt{\frac{1-k}{1+k}}$; (ii) $\pi_P^{N*} \le \pi_P^{R*} < \pi_P^{L*}$ when $\sqrt{\frac{1-k}{1+k}} \le \lambda < \sqrt{\frac{4(1-k)}{3(1+k)}}$; and (iii) $\pi_P^{N*} < \pi_P^{L*} \le \pi_P^{R*}$ when $\sqrt{\frac{4(1-k)}{3(1+k)}} \le \lambda < \sqrt{\frac{2(1-k)}{1+k}}$. □

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