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Optimal Power Structure and Operational Incentives in Live-Streaming Commerce: A Game-Theoretic Analysis of Streamer Influence

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Abstract

The rapid evolution of live-streaming commerce has reshaped retail supply chains, shifting market dominance from manufacturers to influential streamers. Despite this shift, the internal mechanisms of selling efforts and paid traffic acquisition remain underexplored. To bridge this theoretical gap, we develop a game-theoretic framework to model the endogenous power structure and compare the streamer-led top-tier (KS) mode and the brand-led ordinary (MS) mode. Our analytical results reveal three key theoretical insights. First, we establish strict positive monotonicity between streamer influence and equilibrium decisions. Regardless of the power structure, an increase in influence consistently drives the streamer to intensify operational inputs while simultaneously inducing the brand to raise the direct selling price. Second, consumer sensitivity acts as a positive driver of the top-tier mode. Higher sensitivity motivates the streamer to scale up sales efforts and paid-traffic volume, which corresponds to an optimal increase in the brand's retail price. Moreover, the top-tier mode exhibits negative sensitivity to operational costs. We prove that rising costs lead to a significant reduction in the streamer's operational portfolio and, consequently, to a decrease in the brand's price, indicating that the high-input equilibrium is constrained by cost frictions. From a managerial perspective, numerical experiments reveal not a "Consensus on Scale" but a "Conflict on Structure." Specifically, brands maximize profit by collaborating with top-tier streamers, while streamers maximize profit by attaining top-tier influence. However, the brand receives more profit by relinquishing channel leadership with respect to the decision hierarchy. In contrast, the streamer is less profitable as a leader than as a follower due to the "leadership trap," in which greater operational burdens outweigh first-mover advantages.

Keywords: live-streaming commerce; game theory; supply chain power structure; streamer influence; contract design; operational incentives



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1. Introduction

The rise of streaming shopping has changed the shopping industry from the original model of e-commerce to one based on interactive selling in real-time, with conversion made immediately via video [1,2]. Streaming shopping also combines entertainment and the purchasing of goods together, creating a "Fan Economy" where the shopping experience is based not on the platform where a person shops but on its KOL (Key Opinion Leader) [3]. The capabilities of top-tier influencers allow for a large amount of product to be sold in a

single session, therefore making these influencers independent distribution centers with a large amount of negotiation power [4]. As a result, there is now a fundamental shift in power in the supply chain [5]. Traditionally, brands acted as Stackelberg leaders in terms of pricing and distribution strategies towards retailers [6]. However, as streamers and KOLs generate significant volumes of private traffic and influence, they increasingly demand pricing authority and the role of strategic leadership over brands [7].

This change in power has created an essential strategic question for the brand: Should they attempt to keep their position as the top player to maintain their profits or give up that position to a top-tier streamer so they can take advantage of all the potential extra sales since top-tier streamers have such an influence over consumers? [8]. The decision is not easy and involves many moving parts. By maintaining control as a branded company, they can avoid being penalized for selling products at too low a price or being forced to accept high-priced product sales [9]; however, they risk limited product sales potential if they fail to leverage everything that the streamer has to offer [10]. Conversely, if they agree to work with a streamer and let them take control of the marketing process, they may receive a tremendous amount of additional sales volume that would not have come to them otherwise; however, they would still need to function as a price follower and accept that they may lose money on every single unit sold [11].

The resolution of this strategic dilemma is made difficult by the imposition of ill-defined operational mechanisms on traffic monetization [12], as traffic sales are not driven by a single variable but by the business owner balancing transparent selling efforts and paid traffic costs [13]. In past supply chain management research [14], marketing input for streamers has generally been treated as a single variable rather than as a content-related marketing element distinct from the capital-related traffic acquisition aspect of marketing input. The failure to distinguish these two variables demonstrates a lack of clarity regarding the internal operational logic of the streamer's marketing efforts. Moreover, even though there is a consensus in the academic literature [15] about the significance of the term "streamer influence," there has yet to be a clear definition of that term within the context of the theory of supply chain stability, particularly concerning the ways in which multiple dimensions of streamer influence shape and enable the development of the "fan economy".

To address these gaps, this investigation presents an analytical approach to understanding the optimal interaction and motivation between parties in a live-streaming supply chain. Specifically, this study is particularly focused on answering three research questions: (1) How does the level of streamer influence affect selling efforts, paid traffic volume, and pricing strategies when under different types of power structures? (2) What effects do consumer sensitivity and operational costs have on brand and streamer optimization decisions and profitability? (3) On what economic grounds should brands relinquish channel leadership to streamers rather than retaining the first-mover advantage? To answer these questions, we analyze two types of power structures within the supply chain: the streamer-led top-tier (KS) mode, where the streamer with high influence acts as the Stackelberg leader [8], and the brand-led ordinary (MS) mode, where the brand retains dominance [16]. In contrast to previous studies, our analytic framework separates the streamer's operational actions such as their level of effort spent on selling items [17] and their volume of paid traffic [18] used to promote their products so that we may compare how the level of streamer influence affects streamers' choice between using selling effort and paid traffic, along with determining which power structure is optimal for the brand.

This research presents three broad contributions to our understanding of the performance of the fan economy. The first contribution is related to the role of influence and its positive, universal nature; we find that regardless of a streamer's level of influence, as streamers have a greater number of consumers who are influenced, there will be greater

demand on the part of the streamer to improve selling effort level and paid traffic volume. Furthermore, the fan economy demonstrates that consumer sensitivity acts as an efficiency multiplier in the operation of both a top-tier and an emerging brand, and when consumers have high sensitivity to the streamer's non-price attributes, a greater level of selling effort and paid traffic volume will occur simultaneously with an increase in the brand's price. Moreover, we reveal the structural susceptibility of the streamer-led (KS) mode to cost frictions. We find that this high-input system is highly sensitive to operational costs, and friction increases will require a reduction in the streamer's operational portfolio, thereby compelling the brand to lower its prices to reach equilibrium. Finally, our numerical experiments identify the competitive environment as being one of "Consensus on Scale" and "Conflict on Structure". The two parties hold differing views on channel leadership, even though both recognize the importance of maximizing influence. The brand prefers the KS mode because it allows it to capitalize on volume spillover. In contrast, the streamer earns higher profits in the MS mode and avoids the high costs associated with the "Leadership Trap".

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the model formulation and assumptions. Section 4 derives the equilibrium strategies for the KS and MS power structures. Section 5 presents the theoretical analysis and propositions regarding the impact of influence, consumer sensitivity, and operational costs. Section 6 conducts numerical experiments to visualize the strategic insights and delineate the economic boundaries for mode selection. Section 7 discusses the key findings and their practical interpretations. Finally, Section 8 concludes the paper by outlining limitations and directions for future research.

2. Literature Review

Our research is closely related to three streams of literature. Accordingly, this paper will review the literature from three key perspectives: (1) live-streaming commerce and the "Fan Economy," (2) power structures in dual-channel supply chains, and (3) operational effort and traffic acquisition strategies.

2.1. Live-Streaming Commerce and the "Fan Economy"

As the emergence of live-streaming commerce has advanced at a lightning pace, retailer–consumer interactions have evolved from transactional relationships to interactive, live, socially engaged consumers with the retailer. Shang et al. [19] examine the influence of e-commerce live-broadcast background adaptation on consumers' purchase intention and the underlying psychological mechanisms. The results show that the positive effect of perceived value on perceived pleasure is greater than that of perceived trust, although perceived trust is the premise of improving perceived value. Complementing this, Duong et al. [20] apply the theory of trust transfer to describe the evolution of trust created under e-commerce conditions and its impact on customers' overall trust levels regarding purchasing goods from live-streaming channels. The summary of the previous studies indicates that, from a consumer's perspective, trust is created and transmitted via digital networks and is viewed as being transferred from the individual to the company or brand through the consumer's actions and presence on these networks, thereby providing the initial basis for the consumer sensitivity parameter in our model.

The effectiveness of live-streaming as a sales channel is not uniform across streamers due to the large number of different attributes; these attributes vary from streamer to streamer, and thus the impact that a streamer's fans and their ability to influence others is influenced by both the streamer's physical and virtual attributes. Fan & Zhang [21] provide evidence of variability within the KOL-based market by examining how short

video and live-streaming are integrated into commerce and how this affects both KOLs and manufacturers' abilities to charge premium prices for their products. In this study, it was found that high-influence KOLs can help manufacturers charge higher prices for their products, while low-influence KOLs force manufacturers to take different strategic actions. Chen et al. [22] elaborate this further by analyzing a dataset of over 55,000 shows to find that a large fan base does not always help, as the positive effect of fan base exists conditionally. Moreover, the definition of a "streamer" is expanding. Gao et al. [23] found that "coolness factors" of virtual streamers drive purchase intention. At the same time, S. Liu et al. [24] studied the partial and full uncertainty elimination effects of AI avatar streamers and real human streamers, respectively. In general, published research confirms the view that "streamer influence" is a multidimensional variable with a structural impact on value creation.

Differences in streamer influence and consumer sensitivity will result in strategic supply chain configurations, such as channel leadership and marketing modes, being determined endogenously. Wan et al. [25] used a Stackelberg game to discover how a streamer's social influence will determine what type of marketing strategy will yield optimal results. Similarly, Xin et al. [26] find that when consumers react positively to live-streamed products, it is beneficial for the brand to employ specialized live-streaming. Ji et al. [27] broaden the application of live channel pricing strategies; they find that decision-makers are more likely to offer a live channel promotion and raise the price of the traditional online channel under the dynamic price scheme. K. Li et al. [28] indicate that live-streaming channels attract consumers with high patience and encourage their engagement.

Even though there has been much investigation into operational strategy and consumer behavior, a common theoretical framework does not exist in the literature to quantitatively combine streamer influence (τ) and consumer sensitivity (γ) with supply chain equilibrium models. The previous literature acknowledges the significance of the fan economy but has not adequately explored how both core parameters work together to create a "Scale Effect" on operational inputs and to drive the "Efficiency" of value creation.

2.2. Power Structures in Supply Chains

The hierarchy of decision-making authority within a supply chain serves as the primary governance cause of profit allocation and operational efficiency, which is referred to as power structures. Prior to the evolution of supply chain research from static analyses of supply chain power structures and single decision-maker types to analyses of the strategic impact of different channel leaders within dynamic operational and informational environments, supply chain research focused on static power structures and single decision-maker types. Historically, supply chain studies have been concentrated on three configurations of supply chains: manufacturing Stackelberg, retailing Stackelberg, and Vertical Nash. The objective of these studies has been to identify which configuration yields the best result for specific supply chain members.

Supply chain members' preference for a particular power model will shift as a result of changes in the dynamics of the marketplace and from outside influences, including knowledge of inventory policies and levels of transparency in the supply chain. M. Li & Mizuno [29] examined this premise using a periodic review system and discovered that the manufacturers prefer the manufacturer Stackelberg structure when the wholesale price is high. In contrast, when the wholesale price is low, the manufacturers prefer to operate under the Vertical Nash structure. Hu et al. [30] reveal that information asymmetry affects dual-channel supply chains differently, depending on the power structure of each member in a dual-channel supply chain. Wu et al. [31] find that the introduction of big data-driven credit payment services creates a divergence in preferences; generally, retailers

experience positive benefits from this development; however, manufacturers' preferences for either a manufacturer Stackelberg or retailer Stackelberg will fluctuate, depending upon whether the trade-off leans toward opportunity costs or consumer demand. Wang et al. [32] extended this concept to group decision-making and investigated a two-stage consensus feedback mechanism that accounts for different power structures.

Having channel leadership does not assure companies superior profits, which means businesses will sometimes need to relinquish their channel power and focus on maximizing profits. According to Xiao et al. [33], when a retailer finds that store brand introduction is favorable, they may express preferences for power, abdicate power initiatively, or strive to be the game follower to improve profitability. In addition, followers may deliberately engage in misrepresentation in order to defend against dominance from their leader. G. Zhang et al. [34] explore the issue of information misuse in dual-channel sales processes, where followers are often compelled to resort to such practices to counterbalance their leader's power as a means of survival or to gain an advantage. While this type of activity may net the follower personal gain, it also has an adverse effect on the overall profitability of the entire supply chain.

Sustainability mandates and emerging technologies will change how traditional power structures understand one another's relationships. Yuan et al. [35] conducted a study on the adoption of blockchain and discovered that suppliers have strong reasons to adopt blockchain because of its transparency, but retailers' adoption of blockchain will depend on many aspects, such as how convenient consumers find shopping, the preferences of consumers, and where the retailers fit into their competitive landscape. Tao et al. [36] reveal that, under two different supply chain structures, while both suppliers and consumers will benefit from the use of blockchain technology, there are some circumstances under which a supplier may actually have disincentives to maintain high levels of product quality because the use of blockchain technology incentivizes them; therefore, this outcome would ultimately harm the consumer. In the realm of sustainability, N. Zhao et al. [37] state that manufacturer encroachment (a display of power) and low-carbon propaganda provide motivation for manufacturers to increase renewables investments.

While traditional manufacturer Stackelberg and retailer Stackelberg models have been studied intensively, little research has focused on the unique power dynamics of the "Fan Economy" and the trade-offs related to the streamer-led top-tier structure versus the brand-led ordinary structure. Many existing models do not adequately explain why a brand would want to give channel leadership to a high-influence streamer or provide reasonable parameters for defining the boundaries of "Strategic Mode Selection", specifically the exact commission rate threshold (e.g., η) triggering the structural preference transition. This research will close this theoretical gap and provide a thorough explanation of the power dynamics resulting from these constructs, as well as indicate what the ideal business strategy may look like in an economically sensible market environment.

2.3. Operational Effort and Traffic Acquisition Strategies

There are two primary ways to create value from live-streamed media: using both high-quality content and high interaction with audiences to drive sales and controlling the flow of traffic to a live-stream in order to maximize the number of viewers. In traditional retail, "effort" can be viewed as the total cost related to increasing demand for a product. There are, however, many different variables (both internal and external) that contribute to the actual value created and assigned to each of the activities that constitute a live-stream. Therefore, researchers are increasingly interested in understanding these complex relationships, and recent research has improved our understanding of how to convert viewers through internal "effort" and attract audiences through external strategies.

The effectiveness of selling is now more reliant on the balance of providing entertainment versus information, both of which will increase consumer immersion but also lead to increased risk for the company's operations. Gu et al. [38] found that the streamer's expected profit per attending consumer first decreases and then increases with higher entertainment bandwidth, forming a U-shaped relationship. Lv et al. [39] indicate that informativity, entertainment, and interactivity all had a positive effect on immersion, and immersion had a positive effect on viewers' interest in tourism products and live-streaming. Feng et al. [40] found that live social interactions have a "persuasion effect" that negatively influences customers' behaviors in terms of product returns. Wang et al. [41] found that the moderating effect of intelligent recommender systems on the relationship between perceived value and engagement with live-streaming, as well as purchase intention, was positive, whereas the moderating effect of intelligent recommender systems on the relationship between perceived cost and purchase intention was negative.

New traffic acquisition methodologies have surpassed traditional advertising, employing non-price mechanisms and hybrid approaches that leverage content creation strategies; however, streamers' ability to actively acquire traffic through these methods is highly dependent on their existing level of influence. W. Zhang et al. [12] show that "lucky draws" (or sweepstakes) are popular tools for increasing traffic, and while they may increase sales immediately after being promoted, the negative impacts of removing the promotion on future buyer behavior may outweigh the positive effects. The benefit from a lucky draw is based on the popularity of the streamer promoting the lucky draw. Streamers who are less well-known are more likely to see an increase in customer purchases than top-tier streamers. K. Zhao et al. [42] examine the phenomenon of "content switching" on platforms such as Twitch, identifying both direct (positive) spillover from new streamers to viewers (direct spillover) and indirect (positive) spillover through increased visibility of that category (indirect spillover). Zheng et al. [43] explore that e-commerce online retailers should investigate what really engages purchasers rather than simply relying on "likes" as a proxy for engagement, since their analysis reveals that "like" behaviors produced no statistically significant results in actual customer acquisition.

As supply chains face increasing complexity in aligning their operational incentives with mitigating any agency issues, hybrid commitment models and dynamic compensation plans are starting to be adopted to assist with screening for the capability of streamers. Xiao et al. [17] investigate how commitments affect both parties (i.e., sellers and live-streamers). They demonstrate that a commitment to sales efforts benefits both parties. Furthermore, hybrid commitments motivate sellers to store larger quantities of inventory and elicit greater effort from live-streamers than either a sales commitment or an effort commitment alone. Live-streamers consistently prefer hybrid commitments, whereas sellers prefer sales-only commitments. Yang et al. [44] find that well-structured incentive plans can help eliminate poor-performing streamers and also bring in high-talent streamers. Du et al. [45] demonstrate that if a live-streaming channel does not meet the minimum required level of the streamer's sales ability and potential consumer size of the live-streaming channel to the total consumer size, it would turn negative for the manufacturer to integrate that channel into their business practices.

While empirical studies provide rich details on streamer behaviors, theoretical models rarely integrate both "Selling Effort" (θ) and "Paid Traffic Volume" (δ) as simultaneous decision variables subject to convex costs. Consequently, the literature has not yet systematically linked these operational dimensions to the supply chain's cost sensitivity. Specifically, how the operational cost coefficients (C_1, C_2) constrain the optimal strategies in the high-input KS mode remains unclear. There is a lack of analytical modeling that investigates how these cost frictions interact with streamer influence to determine the stability of the equilibrium. This paper integrates these operational decisions into a game-theoretic framework to

examine the sensitivity of optimal strategies to cost shocks and to derive implications for lowering operational friction (Table 1).

Table 1. Summary of key studies related to this study.

Key Related Studies	Streamer Influence	Consumer Sensitivity	Streamer Sales Effort	Traffic Acquisition	Pricing and Incentive Strategy	Power Structure
Shang et al. [19]		✓				
Duong et al. [20]		✓				
Fan & Zhang [21]	✓				✓	
Chen et al. [22]	✓					
Gao et al. [23]		✓				
S. Liu et al. [24]		✓				
Wan et al. [25]	✓					
Xin et al. [26]		✓				
Ji et al. [27]					✓	
K. Li et al. [28]	✓	✓				
M. Li & Mizuno [29]					✓	✓
Wu et al. [31]						✓
Xiao et al. [33]						✓
Zhao et al. [37]						✓
Gu et al. [38]			✓			
Lv et al. [39]			✓			
Feng et al. [40]		✓	✓			
W. Zhang et al. [12]	✓			✓		
K. Zhao et al. [42]				✓		
Xiao et al. [17]			✓		✓	
Yang et al. [44]			✓		✓	
This study	✓	✓	✓	✓	✓	✓

Note: The symbol “✓” indicates that the specific topic is addressed in the referenced study.

3. Problem Description

3.1. Notations

To facilitate the subsequent model formulation and analysis, Table 2 summarizes the key parameters and decision variables used in our model.

Table 2. Notations and explanations.

Parameters	Definitions
a	Base market share of the direct channel ($0 < a < 1$)
$1 - a$	Base market share of the live-streaming channel
c	Unit production cost of the product
η	Commission rate paid to the streamer ($0 < \eta < 1$)
λ	Price discount rate in the live-streaming channel ($0 < \lambda < 1$)
β	Cross-price sensitivity coefficient ($0 < \beta < 1$)
γ	Consumer sensitivity to streamer's non-price attributes (fan economy intensity)
τ	Streamer's inherent influence (τ_H : top-tier streamer, τ_L : ordinary streamer)
C_1	Cost coefficient of selling effort
C_2	Cost coefficient of paid traffic volume investment
Decision variables	
P_d	Retail price in the direct channel (brand's decision)
θ	Selling effort level (streamer's decision)
δ	Paid traffic volume (streamer's decision)
Dependent variables	
P_s	Retail price in the live-streaming channel, where $P_s = (1 - \lambda)P_d$
D_d	Market demand in the direct channel
D_s	Market demand in the live-streaming channel
π_b	Profit of the brand
π_s	Profit of the streamer
π_{sc}	Total profit of the supply chain
Superscripts	
KS	Streamer-led mode
MS	Brand-led mode
*	Optimal value

3.2. Problem

We consider a dual-channel supply chain [6] consisting of a single brand (referred to as “the brand”) and a single live-streaming influencer (referred to as “the streamer”). The brand distributes a product through two distinct channels: a traditional direct sales channel (e.g., an official website) and a live-streaming channel hosted by the streamer [46,47]. A core structural characteristic of this supply chain is the linkage in pricing strategies. Consistent with the industry practice where live-streaming is positioned as a discount-driven promotional channel, the retail price in the live-streaming channel, denoted as p_s , is strictly tied to the direct channel price P_d via a discount rate λ , such that $P_s = (1 - \lambda)P_d$. The assumption describes the “Lowest Price” value proposition that forms the core of the fan economy. As per studies conducted to look at “Market Expansion Effects”, it has been demonstrated that top-tier streamers utilize this to create lower pricing through the live-streaming channel [48]. Further to this, while the nominal selling price may appear to remain consistent between different channels, many streamers also provide their viewers with exclusive gifts or other samples (such as “Buy One, Get One Sample”) to effectively reduce the per unit pricing for consumers. This arrangement allows the brand to take advantage of the pricing benefits already created by live commerce but gives the branding company complete control over the base pricing structure.

To capture the market dynamics, we adopt linear demand functions to isolate the specific impacts of price and non-price attributes [49]. The total market base is set to 1, with a (the intrinsic market’s share) representing the part of the direct channel and $1 - a$ representing the part of the live-streaming channel [50]. As price differences can affect consumer purchasing decisions, these effects are measured using the cross-price sensitivity coefficient β [51]. A key component of our model has been the endogenizing of the “Fan Economy” in the demand for live-streaming. In addition to price, we believe that demand is affected by the streamer influence (τ) [52], the selling efforts level (θ) [53], and paid traffic volume (δ) [54]. Thus, our definition of the demand functions for the direct channel (D_d) and for the live-streaming channel (D_s) explains the effects of these inputs:

$$D_d = a - P_d + \beta P_s \quad (1)$$

$$D_s = (1 - a) - P_s + \beta P_d + \gamma(\tau + \theta) + \delta \quad (2)$$

The parameter τ in Equation (2) represents the level of influence on the streamer as it is used to classify streamer types based upon the structural criterion of influencer types. The top-tier streamer ($\tau = \tau_H$) has a high level of influencer type while the ordinary streamer ($\tau = \tau_L$) has a low level of influencer type ($\tau_H > \tau_L$) [52]. The parameter $\gamma(\tau + \theta)$ in this equation is defined with respect to the demand created by the organic fan base and indicates that the streamer’s effort to sell (θ) is magnified by their natural level of influence (τ) and their fans’ sensitivity (γ). In contrast, paid traffic volume (δ) is modeled as an additive term independent of γ . This specification reflects that paid traffic is a straightforward purchase of exposure from the platform that causes an increase in visibility automatically, with no effect from the existing fan base’s sensitivity or loyalty.

Regarding the cost structure, the streamer generates revenue solely through a commission rate η paid by the brand but incurs operational costs for marketing activities. To reflect the law of diminishing marginal returns, we model these costs as convex quadratic functions. The cost of selling effort is given by $\frac{1}{2}C_1\theta^2$, where C_1 represents the cost coefficient of selling effort. Similarly, the cost of acquiring external traffic is $\frac{1}{2}C_2\delta^2$, where C_2 represents the market efficiency.

Based on the demand and cost structures described above, the general profit functions for the brand (π_b) and the streamer (π_s) are formulated as follows:

$$\pi_b = (P_d - c)D_d + ((1 - \eta)P_s - c)D_s \quad (3)$$

$$\pi_s = \eta P_s D_s - \frac{1}{2}C_1\theta^2 - \frac{1}{2}C_2\delta^2 \quad (4)$$

The interaction is modeled as a Stackelberg game under complete information. The sequence of moves is strictly determined by the supply chain power structure, which depends on the streamer's influence type. In the streamer-led top-tier (KS) mode (τ_H), the streamer acts as the leader, moving first to determine the selling effort level θ and paid traffic volume δ ; the brand acts as the follower, observing these decisions and subsequently setting the direct retail price p_d . In contrast, in the brand-led ordinary (MS) mode (τ_L), the brand acts as the leader, moving first to set the direct retail price p_d ; the streamer acts as the follower, observing the price and subsequently determining the selling effort θ and paid traffic volume δ . Figure 1 is a visual representation of the key structural differences: decision sequences and channel interactions for each of the modes (KS and MS). Section 4 covers detailed analyses of equilibrium for both modes.

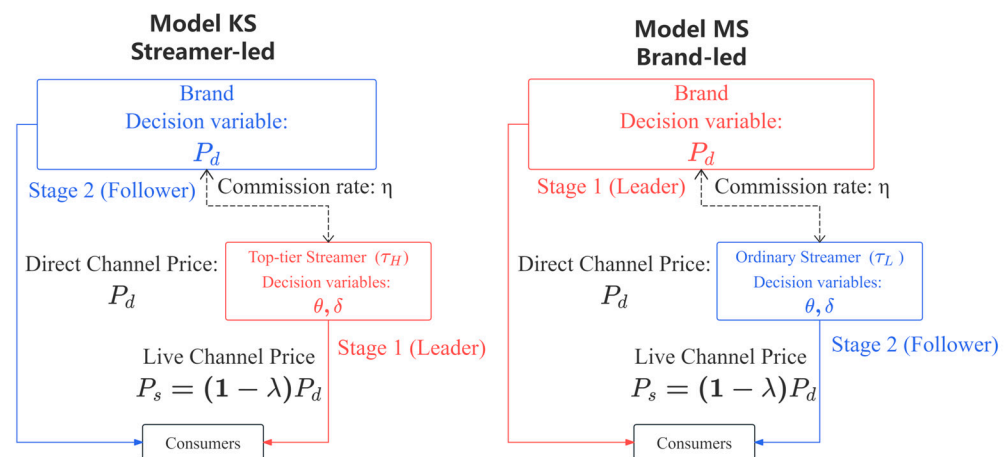


Figure 1. Decision sequences and channel structures in the KS and MS modes.

4. Model Formulation and Optimal Decision-Making

In this chapter, we investigate the equilibrium strategies of the supply chain members under two distinct power structures: the streamer-led top-tier mode (KS) and the brand-led ordinary mode (MS). We utilize a Stackelberg game framework to model the strategic interaction between the brand and the streamer. The solution concept employed is the Subgame Perfect Nash Equilibrium, derived by backward induction. We first analyze the scenario where a top-tier streamer (τ_H) acts as the leader, corresponding to the KS mode, followed by the scenario where the brand acts as the leader over an ordinary streamer (τ_L).

4.1. Streamer-Led Top-Tier Mode (KS)

In the streamer-led top-tier mode (KS), the streamer acts as the Stackelberg leader with high influence (τ_H), while the brand acts as the follower. The decision sequence dictates that the streamer first determines the optimal selling effort (θ) and paid traffic volume (δ), anticipating the brand's pricing reaction; subsequently, the brand sets the direct retail price (P_d).

To explicitly capture the market power of the top-tier streamer, the demand function for the live-streaming channel (from Equation 2) is instantiated with the high influence

parameter $\tau = \tau_H$. Thus, the effective demand functions faced by the supply chain in the KS mode are:

$$D_d^{KS} = a - p_d^{KS} + \beta p_s^{KS} \quad (5)$$

$$D_s^{KS} = (1 - a) - p_s^{KS} + \beta p_d^{KS} + \gamma(\tau_H + \theta^{KS}) + \delta^{KS} \quad (6)$$

We solve the game using backward induction. In the second stage, given the streamer's decisions, the brand determines the retail price to maximize its profit. The brand's optimization problem in the KS mode is given by:

$$\pi_b^{KS} = (p_d^{KS} - c)D_d^{KS} + [(1 - \eta)p_s^{KS} - c]D_s^{KS} \quad (7)$$

In the first stage, the streamer acts as the leader, choosing the optimal operational inputs to maximize her profit while anticipating the brand's response. The streamer's optimization problem is:

$$\pi_s^{KS} = \eta p_s^{KS} D_s^{KS} - \frac{1}{2}C_1(\theta^{KS})^2 - \frac{1}{2}C_2(\delta^{KS})^2 \quad (8)$$

To ensure that the derived solution represents a unique profit-maximizing point rather than a saddle point, we require that the second-order sufficiency conditions hold. Specifically, the Hessian matrix of the streamer's profit function with respect to the decision variables θ and δ must be negative definite. This requires that the principal minors satisfy $H_1 < 0$ and $H_2 > 0$, implying that the operational cost coefficients C_1 and C_2 are sufficiently large relative to the revenue sensitivity parameters to ensure strict concavity.

Proposition 1. *In the streamer-led top-tier mode (KS), provided that the Hessian matrix is negative definite, the unique Subgame Perfect Nash Equilibrium strategies for the streamer's selling effort, paid traffic volume, and the brand's direct retail price are given by:*

$$\theta^{KS*} = - \frac{C_2\gamma\eta(-1+\lambda)(c(-1+\beta)(1+\beta(-1+\lambda))(-2+\lambda) + a(-2+\eta^2(-1+\lambda)^3 + \beta(-1+\lambda)(-2+(-4+\eta)\eta(-1+\lambda)+3\lambda) + \lambda(5+(-3+\lambda)\lambda) - 2\eta(-1+\lambda)(2+(-2+\lambda)\lambda)) - (-1+\eta)(-1+\lambda)(-3+\beta(-3+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda)(1+\gamma\tau_H))}{-C_2\gamma^2(-1+\eta)\eta(-1+\lambda)^2(-3+\beta(-3+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda) + C_1(-((-1+\eta)\eta(-1+\lambda)^2(-3+\beta(-3+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda)) + 2C_2(-2+\beta(-2+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda)^2)} \quad (9)$$

$$\delta^{KS*} = - \frac{C_1\eta(-1+\lambda)(c(-1+\beta)(1+\beta(-1+\lambda))(-2+\lambda) + a(-2+\eta^2(-1+\lambda)^3 + \beta(-1+\lambda)(-2+(-4+\eta)\eta(-1+\lambda)+3\lambda) + \lambda(5+(-3+\lambda)\lambda) - 2\eta(-1+\lambda)(2+(-2+\lambda)\lambda)) - (-1+\eta)(-1+\lambda)(-3+\beta(-3+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda)(1+\gamma\tau_H))}{-C_2\gamma^2(-1+\eta)\eta(-1+\lambda)^2(-3+\beta(-3+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda) + C_1(-((-1+\eta)\eta(-1+\lambda)^2(-3+\beta(-3+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda)) + 2C_2(-2+\beta(-2+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda)^2)} \quad (10)$$

$$p_d^{KS*} = \frac{C_2\gamma^2(-1+\eta)\eta(a+c(-1+\beta)(-2+\lambda))(-1+\lambda)^2 + C_1((-1+\eta)\eta(a+c(-1+\beta)(-2+\lambda))(-1+\lambda)^2 - 2C_2(-2+\beta(-2+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda) \times (1+c(-1+\beta)(-2+\lambda) + \gamma\tau_H - \eta(-1+\lambda)(-1+a-\gamma\tau_H) + \lambda(-1+a-\gamma\tau_H)))}{-2C_1(-1+\eta)\eta(-1+\lambda)^2(-3+\beta(-3+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda) - 2C_2\gamma^2(-1+\eta)\eta(-1+\lambda)^2(-3+\beta(-3+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda) + 4C_1C_2(-2+\beta(-2+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda)^2} \quad (11)$$

The proof is relegated to Appendix A.1.

The equilibrium strategies derived in Proposition 1 illuminate the strategic distinctiveness of the streamer-led power structure, where the top-tier streamer acts as a dominant strategic driver rather than a passive sales agent. Unlike the ordinary follower in the MS mode, the leader in the KS mode internalizes the brand's pricing reaction function into their optimization problem, thereby strategically pre-committing to specific levels of selling

effort (θ^{KS*}) and traffic investment (δ^{KS*}). The analytical solution reveals that the streamer's high influence (τ_H) functions as a structural multiplier, amplifying the marginal revenue product of operational inputs and incentivizing aggressive investment despite convex costs. The streamer is predicting that, in response to a surge in demand, the brand will rationally increase the price (P_d^{KS*}) of its product, thereby allowing the streamer to benefit from the additional revenue created by this increased price. As a result, the streamer has positioned the supply chain to operate within a "high value", "high demand" environment. In this way, the streamer is able to maximize the potential of the "Fan Economy" (γ) compared to the established margins-driven model of pricing.

4.2. Brand-Led Ordinary Mode (MS)

In the brand-led ordinary mode (MS), the MS model has a balance of power with the brand and streamers who have little influence in this model (τ_L). The decision sequence is reversed compared to the KS mode. The brand acts as the Stackelberg leader, first determining the direct retail price (P_d); subsequently, the streamer acts as the follower, observing the price and determining the optimal selling effort (θ) and paid traffic volume (δ).

Reflecting the limited capability of the ordinary streamer, the live-streaming demand function incorporates the low influence parameter $\tau = \tau_L$. Consequently, the specific demand functions in the MS mode are expressed as:

$$D_d^{MS} = a - P_d^{MS} + \beta P_s^{MS} \quad (12)$$

$$D_s^{MS} = (1 - a) - P_s^{MS} + \beta P_d^{MS} + \gamma(\tau_L + \theta^{MS}) + \delta^{MS} \quad (13)$$

We solve the game using backward induction. In the second stage, observing the brand's pricing decision, the ordinary streamer determines her operational inputs to maximize her own profit. The streamer's optimization problem in the MS mode is given by:

$$\pi_s^{MS} = \eta P_s^{MS} D_s - \frac{1}{2} C_1 (\theta^{MS})^2 - \frac{1}{2} C_2 (\delta^{MS})^2 \quad (14)$$

To ensure that the streamer's reaction functions yield a unique maximum, we require the second-order sufficiency conditions to be satisfied. The Hessian matrix of the streamer's profit function with respect to θ and δ must be negative definite. Similar to the KS mode, this implies that the operational cost coefficients must satisfy specific conditions ($H_1 < 0$ and $H_2 > 0$) to guarantee strict concavity.

In the first stage, the brand acts as the leader, anticipating the streamer's reaction functions $\theta^*(P_d)$ and $\delta^*(P_d)$. The brand chooses the optimal retail price to maximize its total profit from both channels. The brand's optimization problem is:

$$\pi_b^{MS} = (P_d^{MS} - c) D_d^{MS} + [(1 - \eta) P_s^{MS} - c] D_s^{MS} \quad (15)$$

Proposition 2. In the brand-led ordinary mode (MS), the unique Subgame Perfect Nash Equilibrium strategies for the brand's direct retail price (P_d^{MS*}), the streamer's selling effort (θ^{MS*}), and paid traffic volume (δ^{MS*}) are given by:

$$\theta^{MS*} = \frac{\gamma\eta(-1+\lambda)(cC_1\eta(-1+\lambda)+cC_2\gamma^2\eta(-1+\lambda)+C_1C_2(1+c(-1+\beta)(-2+\lambda)+\gamma\tau_L-\eta(-1+\lambda)(-1+a-\gamma\tau_L)+\lambda(-1+a-\gamma\tau_L)))}{C_1(-2C_1(-1+\eta)\eta(-1+\lambda)^2-2C_2\gamma^2(-1+\eta)\eta(-1+\lambda)^2+2C_1C_2(-2+\beta(-2+\eta)(-1+\lambda)+\eta(-1+\lambda)^2-(-2+\lambda)\lambda))} \quad (16)$$

$$\delta^{MS*} = \frac{\eta(-1+\lambda)(cC_1\eta(-1+\lambda) + cC_2\gamma^2\eta(-1+\lambda) + C_1C_2(1+c(-1+\beta)(-2+\lambda) + \gamma\tau_L - \eta(-1+\lambda)(-1+a-\gamma\tau_L) + \lambda(-1+a-\gamma\tau_L)))}{C_2(-2C_1(-1+\eta)\eta(-1+\lambda)^2 - 2C_2\gamma^2(-1+\eta)\eta(-1+\lambda)^2 + 2C_1C_2(-2+\beta(-2+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda))} \quad (17)$$

$$P_d^{MS*} = - \frac{cC_1\eta(-1+\lambda) + cC_2\gamma^2\eta(-1+\lambda) + C_1C_2(1+c(-1+\beta)(-2+\lambda) + \gamma\tau_L - \eta(-1+\lambda)(-1+a-\gamma\tau_L) + \lambda(-1+a-\gamma\tau_L))}{-2C_1(-1+\eta)\eta(-1+\lambda)^2 - 2C_2\gamma^2(-1+\eta)\eta(-1+\lambda)^2 + 2C_1C_2(-2+\beta(-2+\eta)(-1+\lambda) + \eta(-1+\lambda)^2 - (-2+\lambda)\lambda)} \quad (18)$$

The proof is relegated to Appendix A.2.

The equilibrium strategies derived in Proposition 2 highlight the structural passivity of the ordinary streamer in the MS mode. Unlike the KS mode, where the leader strategically pre-commits to operational levels to shape the market, the ordinary streamer's optimal effort (θ^{MS*}) and traffic (δ^{MS*}) are derived from best-response functions conditional on the brand's retail price (P_d^{MS*}). The analytical solution indicates that the streamer's marketing intensity is strictly constrained by operational efficiency and the marginal revenue dictated by the brand's pricing signal. Lacking the high influence (τ_L) to induce the brand into a volume-centric strategy, the ordinary streamer adopts a reactive stance. In establishing retail pricing to maximize direct channel margins, the brand treats live-streaming as a distribution channel supplemental to its retail channel (not the primary source of profit). In the absence of an influence multiplier effect, the supply chain reverts to a traditional brand-centric hierarchy, thereby limiting streamers' ability to drive market growth, as they lack the authority to make strategic promotional decisions.

5. Model Analysis

The following will present an in-depth analysis regarding how three market parameter types affect optimal decision-making within the live-streaming environment: streamer influence (τ), consumer sensitivity (γ), and operational costs (C_1 & C_2). The quantitative comparison will provide a view of the equilibrium strategies (including direct pricing P_d , selling effort level θ , and volume of paid traffic δ). By decoupling the studies based on the two power structures (KS and MS), it will be possible to identify what specifically will be the operational mechanisms that will create value for each of the live-streaming supply chains.

5.1. Impact of Streamer Influence

The nature of the streamer's influence (τ), where they can drive traffic, and their fan base are the primary differentiating factors that determine the streamer's market position. To identify the baseline "Scale Effect," we will establish how variations in streamer influence (τ) have an impact on both of the power structures and have an effect on the optimal operational strategies for each of the two power structures used by streamers.

Proposition 3. *Regardless of the specific power structure, an increase in streamer influence consistently acts as a positive driver for operational inputs and retail prices. Specifically, the optimal direct price, selling effort, and paid traffic volume exhibit strict monotonicity with respect to influence in both modes.*

(i) In the KS mode:

$$\frac{\partial P_d^{KS*}}{\partial \tau_H} > 0, \quad \frac{\partial \theta^{KS*}}{\partial \tau_H} > 0, \quad \frac{\partial \delta^{KS*}}{\partial \tau_H} > 0 \quad (19)$$

(ii) In the MS mode:

$$\frac{\partial P_d^{MS*}}{\partial \tau_L} > 0, \quad \frac{\partial \theta^{MS*}}{\partial \tau_L} > 0, \quad \frac{\partial \delta^{MS*}}{\partial \tau_L} > 0 \quad (20)$$

The proof is relegated to Appendix A.3.

In proposition 3, the influence of streamers is regarded as a universal “scale multiplier” that transcends the hierarchy of power. Economic logic shows that there is a strong “asset-flow complementarity” between the streamer’s social capital (influence) and operational traffic. The influence of streamers has improved the marginal output of enterprise marketing input. If the streamer has top-tier influence, the effort to convert paid traffic into sales will be much greater than that of the streamer with low influence. Therefore, maximizing profits through rational and profit-maximizing choices can not only increase the volume of operating activities but also maximize revenue. Regardless of the decision-making order in the “scale strategy”, the inherent participation of a larger fan base will naturally increase the participation.

In addition, due to the expansion of the scope of operation, the scope of operation of streaming media companies provides more positive “positive spillover” for the brand’s pricing strategy. The increase in marketing activities, driven by rising streamer sales and paid traffic, has significantly shifted the overall demand curve upward. This upward movement is called the “demand expansion effect”; that is, the trade-off between brand profits and sales is significantly reconfigured. Due to the influence of anchors, brand products have attracted more potential consumers, and the elastic constraints of brand demand have become smaller. Therefore, brands can increase direct sales prices and derive substantial value from streamers’ influence while maintaining high sales. Therefore, price increases generally pull all members of the supply chain into the “high-flow and high-value balance”, further strengthening the premise that inherent influence is the first driving force of market size.

5.2. Impact of Consumer Sensitivity

The intensity of the “Fan Economy” is captured by the parameter (γ), which reflects the extent to which consumers value the streamer’s non-price qualities and the effort they invest in engaging with it. This situation informs our theoretical approach to how “Sensitivity to Fan Engagement” drives the decision-making process of a top-tier streamer (τ_H), whose powerful influence network causes the system to respond strongly to consumer engagement factors.

Proposition 4. *In the KS mode, an increase in consumer sensitivity (γ) serves as a global multiplier for value generation. Consequently, as consumer sensitivity increases, the optimal selling effort level, paid traffic volume, and direct pricing will be strictly positively monotonically correlated to consumer sensitivity:*

$$\frac{\partial P_d^{KS*}}{\partial \gamma} > 0, \quad \frac{\partial \theta^{KS*}}{\partial \gamma} > 0, \quad \frac{\partial \delta^{KS*}}{\partial \gamma} > 0 \quad (21)$$

The proof is relegated to Appendix A.4.

Proposition 4 outlines the “Amplifier” mechanism of the fan economy, showing how sensitivity reveals previously hidden economic value from influences. By possessing a large fanbase that can respond to the high-level of influence, consumer sensitivity acts as a multiplying factor or conversion efficiency multiplier for all the different types of monetization techniques that the streamer uses. Consumers with a greater “sensitivity” will be more significantly impacted by the product that’s available through the streamer. The “high” marginal utility created for fans by their streaming and social media activities

will turn those fans into actual buyers. With increasing marginal returns and a greater reliance on the “Aggressive Operational Posture,” the streamer has intensified its internal sales efforts and its external traffic acquisition efforts as it expands its market. The result has been positive feedback on the interplay between these two types of operational intensities, which is driving the maximal monetization of the streamer’s influence assets.

Correspondingly, as a result of increased momentum in operational activities, the brand is positioned to benefit strategically from “Price-Volume Leverage.” The brand has lost its “channel leadership” position in KS mode, but by virtue of this loss, the brand is able to take advantage of the tremendous amount of positive “spillover” (ongoing effects) provided by the aggressive expansion of the streamer of operations and traffic, which pushes out on the combined demand curve significantly, thus creating a “Volume Compensation Effect”. The increase in demand essentially mitigates the usual price elasticity faced by the brand, allowing the brand to increase direct sales prices to capture and retain increased surplus value. Therefore, when the supply chain operates in a highly consumer-sensitive environment, this creates a situation where all of its selling effort level (θ^{KS*}), paid traffic volume (δ^{KS*}), and direct pricing (P_d^{KS*}) increase simultaneously at an optimum level referred to as “Performance Equilibrium”.

5.3. Impact of Operational Costs

In addition, we will investigate how sensitive equilibrium strategies are to operational frictions, including the cost coefficient of selling effort (C_1) and the cost coefficient of paid traffic volume (C_2). These two parameters measure the marginal resistance to creating value.

Proposition 5. *In the KS mode, optimal strategies are always negatively sensitive to the operational cost coefficients. In this case, the system is characterized as having a “High-Effort, High-Sensitivity” to operational costs. An increase in either operational cost (C_1 and C_2) will reduce the direct pricing (P_d^{KS*}), selling effort level (θ^{KS*}), and volume of paid traffic (δ^{KS*}) across the supply chain as a whole.*

- (i) *Sensitivity to Selling Effort Cost (C_1): A marginal increase in selling effort cost (C_1) will cause an equally large reduction in all areas: P_d^{KS*} , θ^{KS*} , and δ^{KS*} .*

$$\frac{\partial P_d^{KS*}}{\partial C_1} < 0, \quad \frac{\partial \theta^{KS*}}{\partial C_1} < 0, \quad \frac{\partial \delta^{KS*}}{\partial C_1} < 0 \quad (22)$$

- (ii) *Sensitivity to Paid Traffic Volume Cost (C_2): Likewise, a marginal increase in paid traffic volume cost (C_2) will produce what could be considered a systemic impact; reduction in all strategic decision-making variables across the board: P_d^{KS*} , θ^{KS*} , and δ^{KS*} .*

$$\frac{\partial P_d^{KS*}}{\partial C_2} < 0, \quad \frac{\partial \theta^{KS*}}{\partial C_2} < 0, \quad \frac{\partial \delta^{KS*}}{\partial C_2} < 0 \quad (23)$$

The proof is relegated to Appendix A.5.

In Proposition 5, we show that the KS mode is very sensitive to costs. High-input systems are not only capital-intensive but also require substantial operational inputs to support them across a full range of conditions. Additionally, the KS mode relies heavily on its dominance and large viewership to sustain it. Therefore, due to the mathematically derived results, any increase in friction (C_1 and C_2) results in a reconfiguration across its entire operational portfolio, not just within the given localized market space, to preserve its profitability margins.

Furthermore, operational contraction can further lead to a “chainwide” collapse of the entire supply chain. When a streamer reduces its operational inputs ($\theta \downarrow, \delta \downarrow$), this leads to reduced demand, resulting in an inward shift in the aggregate demand curve (the opposite of the expansion effect mentioned in Proposition 4). The brand has no choice but to reduce the selling price of the product (i.e., both direct and spillover sales) to keep pace with the lower volume of sales in order to maintain sales velocity. Proposition 5 shows that while the KS model contains great potential for performance, its effectiveness heavily relies on sufficiently low friction to maintain this equilibrium.

6. Numerical Analysis

In this section, we examine the multiple experiments numerically that were used to validate the theoretical propositions presented in Section 5. By performing this analysis, we can also quantitatively measure the effects of all major market variables, such as streamer influence (τ), consumer sensitivity (γ), operational costs (C_1, C_2), and contract terms (η, λ).

In order to clearly delineate the streamer influence from that of the cooperative mode, our methodology consists of four distinct logical steps. In Section 6.1, a comparison between the KS and MS models will be presented. The disparity between these two models will illustrate the total profits attributable to the enormous amount of streamer influence. In Section 6.2, we have addressed the effects of different forms of streaming on an individual’s experience by identifying where the KS mode would provide the same or similar level of influence as the MS mode through an analysis of the effect of streaming in each mode and providing evidence of a “Leadership Trap” created by KS mode and the “Free-Rider” advantages to a brand. In Section 6.3, we will evaluate when the brand should strategically transition to the KS mode and in what fashion; we will then correlate these analysis results with an economic construct of supply chain members. As the members have a “Consensus on Scale” in terms of accumulating influence but a “Conflict on Structure” in terms of selecting the streaming mode, we will demonstrate how this applies to different types of supply chain relationships.

Based on the literature [52,55,56] and practices found within business, we established our baseline parameter set to guarantee both numerical stability and economic viability. We adopt the following baseline parameter set for our simulations: market share potential $a = 0.6$, production cost $c = 0.2$, cross-price elasticity $\beta = 0.6$, consumer sensitivity $\gamma = 1.3$, commission rate $\eta = 0.3$, discount rate $\lambda = 0.2$, effort cost coefficient $C_1 = 3.0$, and traffic cost coefficient $C_2 = 5.0$. Unless explicitly stated, the numerical stability and economic viability remain constant as all specific parameters are varied to assess the effect on system performance.

6.1. Analysis of Scale Effect: Top Tier vs. Ordinary Streamers

6.1.1. Impact of Consumer Sensitivity

This research directly compares the profitability of a top-tier streamer (KS mode: $\tau_H = 2.0$) to that of an ordinary streamer (MS mode: $\tau_L = 0.1$) in order to explore the impact of consumer sensitivity (γ) on the creation of value at various levels of influence. This allows us to calculate the “Scale Effect” of fan economies.

Figure 2 shows the progression and flow of equilibrium profits for both the brand and the streamer as the sensitivity parameter increases from 0.5 to 2.0. The results confirm what has been expected, namely that the equilibrium profits of all supply chain members grow, though at different rates for the same two supply chains, indicating a very different approach to how each supply chain member delivers value and demonstrating why the top-tier (KS) mode provides so much unique additional value.

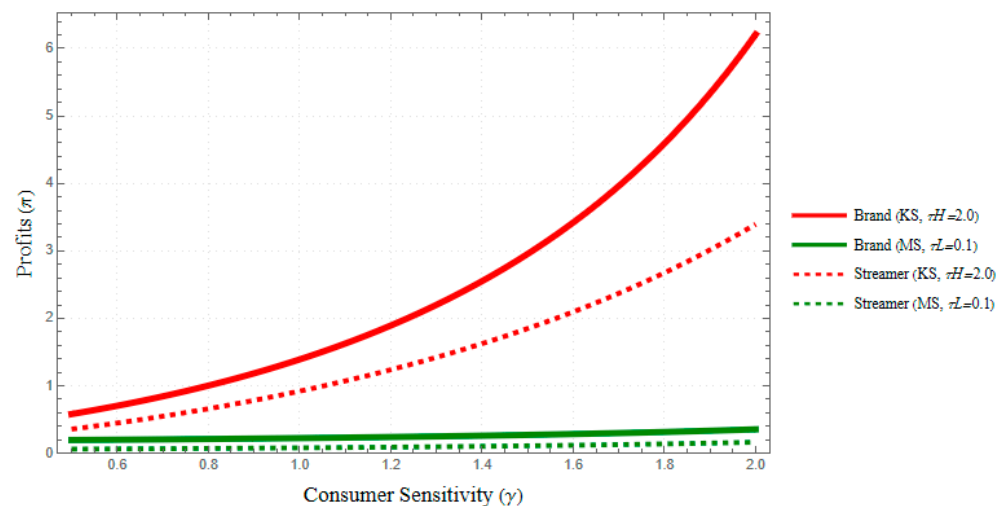


Figure 2. Impact of consumer sensitivity (γ) on the equilibrium profits under different power structures.

The KS structure produces a much faster increase in profit than the MS structure. The profit curves for both the brand and streamer operating with the KS model (red lines) are rapidly rising, resulting in a rapidly widening disparity between them and their MS counterparts (green lines). This analysis concludes that high consumer sensitivity is acting as a strong “multiplier” for the effect of streamer influence. In the KS model, the top-tier streamer has the influence necessary to convert fans’ enthusiasm into real economic value and thus use that high degree of influence to generate substantial profits. The flat trajectory of the MS curves indicates that the opportunities for economic success arising from the fan economy are largely dormant for ordinary streamers without significant influence; therefore, without the catalyst of substantial streamer influence, it is not possible to monetize high consumer sensitivity.

Additionally, the results show higher profits generated for the brand under high consumer sensitivity in the KS model than in the MS model. Therefore, it is reasonable to infer that within those industries where fan engagement is at its peak, the cost of giving up the leadership position for an improved efficiency is significantly lower when compared to the KS structure, which provides access to the “fan dividend” which is not accessible through the MS structure, allowing the brand and the streaming service to both benefit from an increased market surplus.

6.1.2. Impact of Cost Coefficients

Continuing the comparison between top-tier and ordinary streamers, we examine how operational costs impact the supply chain’s profitability. Figure 3a,b depict the impact of the selling effort cost coefficient (C_1) and the paid traffic volume cost coefficient (C_2), respectively. It is expected that all members in the supply chain will experience reduced profits with an increase in one of the cost parameters, but conducting a comparative analysis of the operational drivers for the KS model provides further insights into what is happening within the supply chain among the various tiers.

The results presented in Figure 3a indicate that the top-tier (KS) mode has a sensitivity to the costs associated with exerting selling effort (C_1). Profit curves for the KS system (red lines) are rapidly declining, demonstrating the KS structure functions as a “High-Effort” system—while the top-tier streamer has significant inherent influence, they capitalize on this inherent influence mainly by exerting great amounts of selling effort to attain maximum conversion rates; thus, their profitability is directly affected by the cost efficiency of this effort. Conversely, the ordinary (MS) mode (green lines) exhibits much less variability

of profit curves (being nearly flat) compared to variations of selling effort costs. This indicates that ordinary streamers tend to operate at a low-investment equilibrium due to the limitations of their traffic base; thus, they require less expendable selling effort and, as a result, respond less to cost fluctuations.

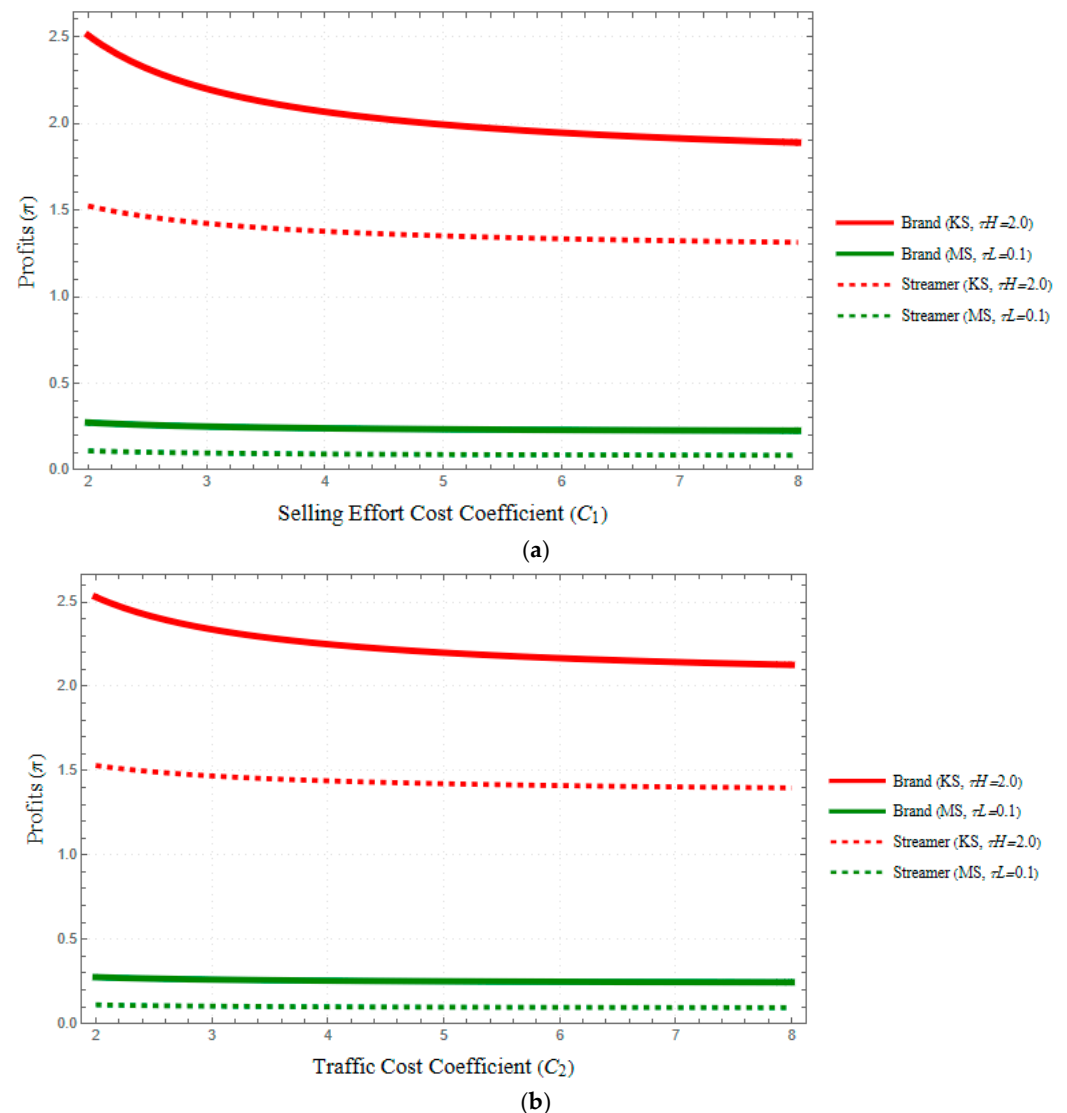


Figure 3. (a) Impact of C_1 on equilibrium profits. (b) Impact of C_2 on equilibrium profits.

The comparison of this graph (Figure 3b) reveals significant differences in profit sensitivity regarding traffic acquisition costs and KS profit margins. The slope of the KS profit margin curve relative to the effort cost scenario indicates that KS profits decrease as their associated acquisition costs rise, but the rate of decrease is much less steep than in the effort cost scenario. As a result of this trend, we can conclude that while the paid traffic volume is one of the contributing factors, it is not the primary driver of top-tier performers' strategies; it is actually the strong organic influence a top-tier performer obtains through their existing fan base that enables top-tier streamers to further concentrate efforts on leveraging their organic stock of influence rather than relying heavily on acquisition of paid traffic. Hence, the outperformance of KS mode(s) can be seen to be largely attributable to the aggressive use of a streamer's organic stock of influence (through the sale of effort) as opposed to the excessive expenditures for paid traffic volume.

Furthermore, the KS mode provides both the brand and the streamer with considerably higher profit levels versus the MS mode in both cases above. This clearly demonstrates the “Scale Effect”: although operational costs are increasing for both the brand and streamer, the substantial influence of the streamer allows KS mode to continue to offer the best value for both the brand and streamer relative to MS mode at this time.

6.1.3. Impact of Contract Parameters

As a means of concluding our discussion on the differences in streamer incidences due to the KS and MS modes, we examine how the type of contract they sign influences the allocation of the surplus generated by streamer influence. The impact of the commission rate (η) and the price discount rate (λ) is visually represented in Figure 4a,b, respectively.

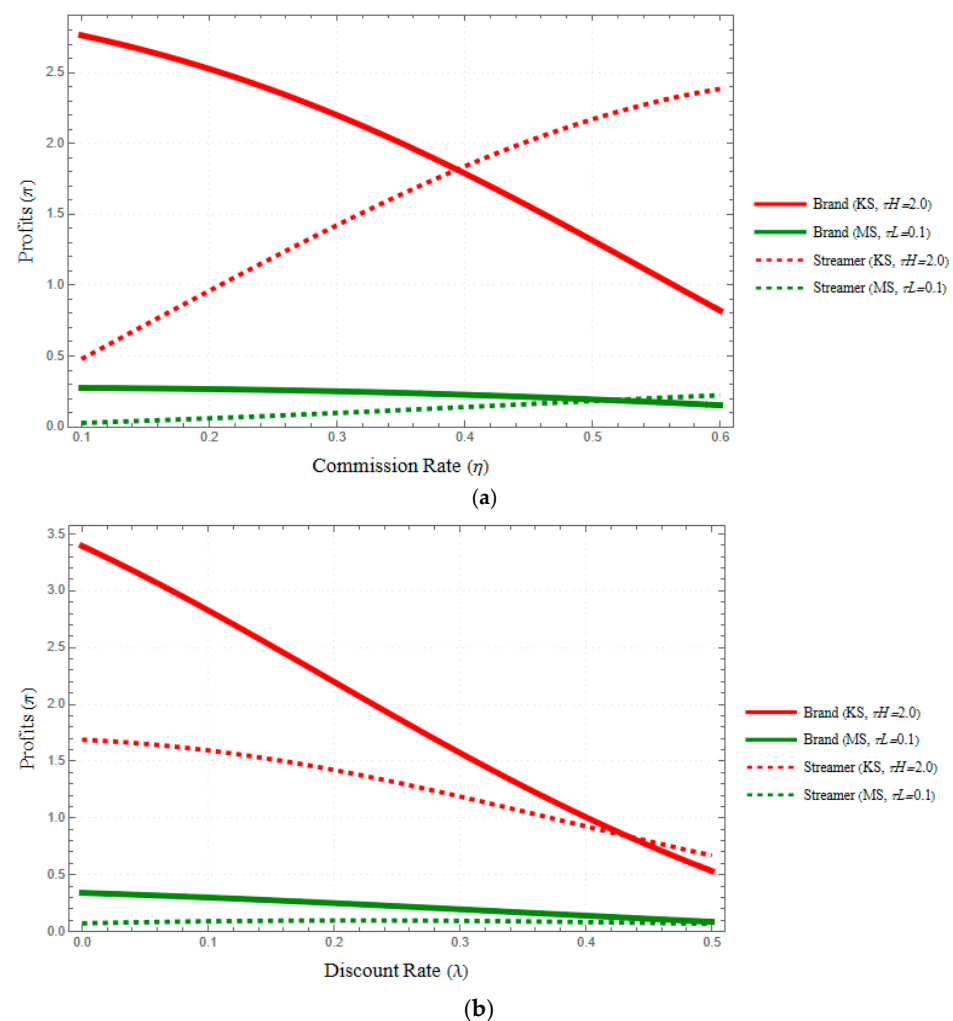


Figure 4. (a) Impact of η on equilibrium profits. (b) Impact of λ on equilibrium profits.

Figure 4a shows a clear difference in the rate of increase in the commission. In the ordinary (MS) mode (green lines), the profits have almost total inertia, with the profit curves being pretty much flat (i.e., no curvature). Therefore, the adjustment of the revenue sharing ratio will have little to no impact on the total system performance of ordinary streamers for the majority of their traffic streams; this is due to the “Influence Constraint”. Conversely, examining the top-tier (KS) mode (red lines), there appears to be a much greater impact on contract terms. As the commission increases in the KS mode, we see a very steep increase in streamer profits and a very steep decrease in brand profits. Throughout all ranges considered, brand profits from the KS mode (red solid line) remain significantly greater than in the

MS mode (green solid line). This demonstrates that the volume compensation effect of the top-tier streamer is indeed strong enough to offset even very large commissions, ensuring that the KS mode is always the superior brand strategy, independent of split amounts.

Figure 4b exposes a vulnerability in the top-tier mode due to discount rate increases. All profits decrease as a function of increasing discount rate (λ) across all models, illustrating that the margin squeeze effect tends to exceed the demand expansion effect overall. However, while the KS mode brand profit curve (red solid line) decreases more rapidly compared to the streamer profit curve, the KS mode streamer generates a huge volume of sales ($\tau_H = 2.0$), causing the marginal reduction in unit price to be multiplied by the huge sales volume and resulting in a dramatic decrease in total brand profit. Thus, at large discount rates, a profit reversal occurs where the streamer will receive a larger amount of profit than the brand. Consequently, the KS model generates added value to the brand by increasing sales volume but also places a significant limitation on the brand's profitability. Therefore, heavy discounting will have a very negative effect on the brand and offset the added value that the brand receives from the partnership.

6.2. Comparative Evaluation of Profitability at Identical Streamer Influence Levels

Pursuant to Section 5, discussing streamer influence being the driving force behind absolute profitability, we turn from the scaling factors previously reviewed to measure how the supportive power structures are operating at internal efficiency. The structural analysis being presented here should be viewed separately from what was presented in Section 6.1 (i.e., Figure 2). In Figure 2, we see a "Top-tier streamer" creating the largest amount of absolute profit in the KS mode through streamers having significantly more influence ($\tau_H \gg \tau_L$). The purpose of the following structural analysis is to compare both modes at equal levels of influence. By doing this, we will effectively hold constant the "Scale Effect" to isolate how structure impacts all participants in the supply chain. The intention of this analysis is to demonstrate how much more a brand's profitability is being diminished relative to first-mover advantage (i.e., "Influence Compensation Effect") as well as to indicate whether the streamers profit from being the leader in the KS mode (i.e., "Leadership Trap").

6.2.1. The Influence on Compensation Effect and the Leadership Trap

A thorough examination of the structural effects on both parties due to this transfer of power requires isolating the role of streamer influence on the guaranteed profit levels of each party. To do so, we keep the commission and all cost factors constant, providing a baseline for comparing the two modes (Figure 5) and supporting our findings regarding the "Influencer Compensation Effect" (for the brand) and the "Leadership Trap" (for the influencer).

Figure 5 illustrates the evolution of optimal profits for both the brand and the streamer as the influence parameter τ increases from 0 to 10. As predicted by our theoretical derivations, the profits for all parties increase monotonically with influence, confirming that an increase in streamer influence significantly enhances the total profitability of the supply chain. However, a comparative analysis at equivalent influence levels reveals that the KS and MS modes have differential impacts on the profits of the brand and the streamer.

For the brand, the numerical results demonstrate a structural dominance: the brand's profit in the KS mode (red solid line) consistently surpasses that in the MS mode (green solid line). It can be concluded that "Influence Compensation" is a well-established concept. The KS mode allows for higher high-volume sales due to the high influence of the streamer, despite the brand not holding the price leadership status as it does under MS mode, which ultimately compensates for the loss of price leadership in that market in the process. The

KS mode essentially provides the brand with an asymmetrical cost structure, whereby the streamer takes greater responsibility for powering the market; however, the majority of the revenue generated will be captured by the brand.

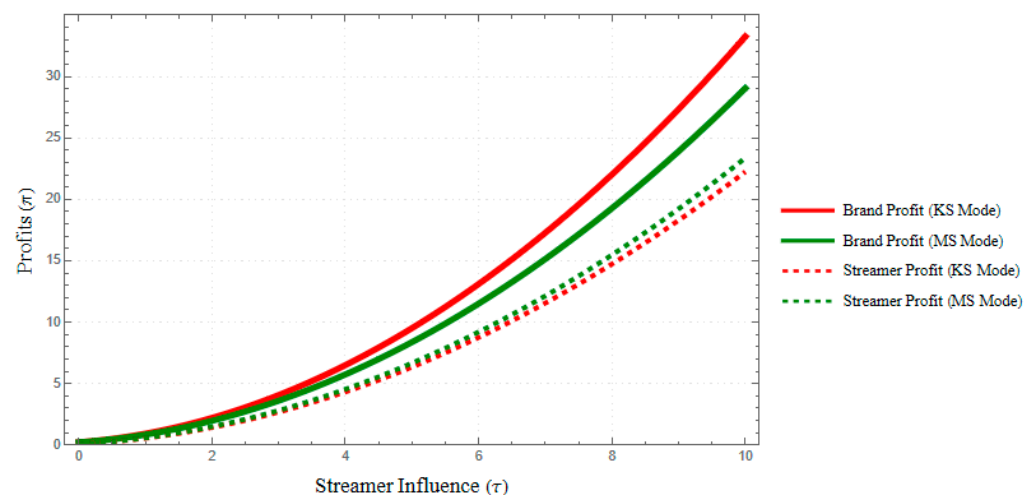


Figure 5. Impact of streamer influence (τ) on the equilibrium profits of the brand and the streamer.

Conversely, there is a clear disconnect between the streamer's profits and that streamer's level of influence in the market, which has produced what we refer to as a "Leadership Trap", specifically for the streamer. Although there is a strategic first-mover advantage based on being in a leadership position, our results indicate that the operational burden that the leadership now carries far exceeds the benefit. When we compare two streamers who are equally influential, the streamer in the KS model makes less profit than the streamer in the MS model (green dashed line). This result was unexpected because of how each decision path incentivizes certain behaviors. In the KS model, the streamer as a leader has an incentive to invest heavily in sales efforts and paid traffic to enhance demand for their product. As such, they have incurred a relatively large amount of operational costs as a result of this investment. In the MS model, however, the streamer operates as a follower. In this position, the streamer optimizes their investment level in response to the brand's wholesale price, leading to a more conservative strategy that avoids the excessive expenditures characteristic of the leadership role.

6.2.2. Profit Distscapes: The Interplay of Influence and Commission Rates

To visualize how the "Scale Effect" and "Structural Efficiency" interact under different contract terms, we synthesize the two critical decision levers—streamer influence (τ) and commission rate (η)—into a 3D profit landscape (Figure 6).

In Figure 6, the red surfaces represent the KS mode, while the green surfaces represent the MS mode. To distinguish between the players, the brand's profits are depicted as solid opaque surfaces, while the streamer's profits are depicted as transparent mesh surfaces. The 3D visualization clearly demonstrates two key findings: the KS mode is consistently the most profitable option for the brand, while the streamer's profit fluctuates significantly depending on the specific parameters.

First, with respect to the brand's profitability, the data indicates that the KS mode consistently yields higher returns than the MS mode. The red solid surface (KS brand profit) is situated consistently above the green solid surface (MS brand profit) across the entire observed range. This observation indicates that the "Influence Compensation Effect" is robust. Whether the partner is a rising star (moderate τ) or a super-influencer (high τ), and regardless of the commission rate (within the feasible range η), the brand maximizes its

absolute profit by delegating channel leadership to the streamer. The KS structure increases efficiency and, therefore, the total surplus created, to the benefit of the brand itself.

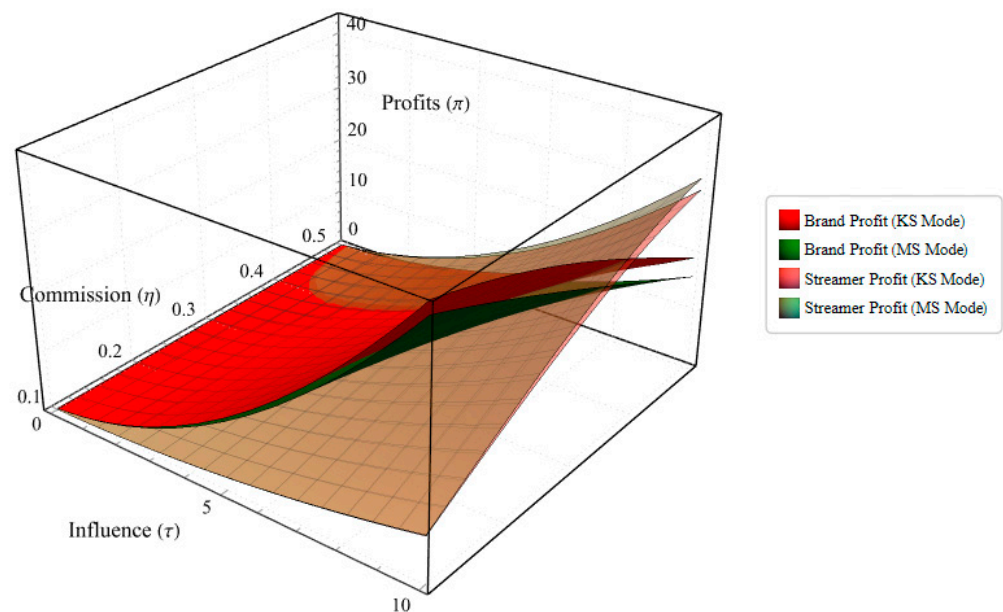


Figure 6. Profit landscape illustration depicting how streamer influence (τ) combined with commission rates (η) impacts the profits of the brand and the streamer across KS and MS modes.

However, at the same time, the distribution of profits from the KS structure undergoes a profound change. A significant effect of this is found when we compare the red solid surface (brand) to the red mesh surface (streamer) and notice that we have a critical inflection point. The inflection point occurs in the lower-left quadrant of the graph (low influence, low commission); the brand is earning substantially more than the streamer (solid > mesh). Nevertheless, as we shift into the maximum end of the streamer influence (high τ), combined with the higher commission rates (high η), we see the red mesh surface rise at a significant rate; eventually, it pierces through the red solid surface and towers over it. In this situation, the streamer would have a greater profit margin than the brand. It appears that in this instance, although the KS mode offers the brand a very high structural efficiency, the streamer gains the title of the primary beneficiary.

6.2.3. System Efficiency and Cooperative Basis

The analysis in Sections 6.2.1 and 6.2.2 reveals an obvious “structural conflict”: the brand side strictly prefers the KS model to obtain influence benefits, while the streamer side often prefers the MS model to avoid the operating costs of the “leadership trap”. This leads to a key question: Is there an economic basis for the two sides to cooperate in the KS model in the case of opposing preferences? To answer this question, we will go beyond the perspective of individual profit and examine the total profit of the supply chain (brand profit + streamer profit).

Figure 7 compares the total profit created by the whole supply chain in two modes. The result is decisive: the orange curve (KS mode) is always above the blue curve (MS mode). With the growth of the influence of the streamer, the gap between the two curves continues to widen. This gap represents “efficiency surplus”—the additional value that can be created by selecting the KS structure alone. This proves that the KS model is more structurally efficient: it can more effectively transform the streamer’s influence into actual market returns, essentially “making the pie bigger” for the whole system.

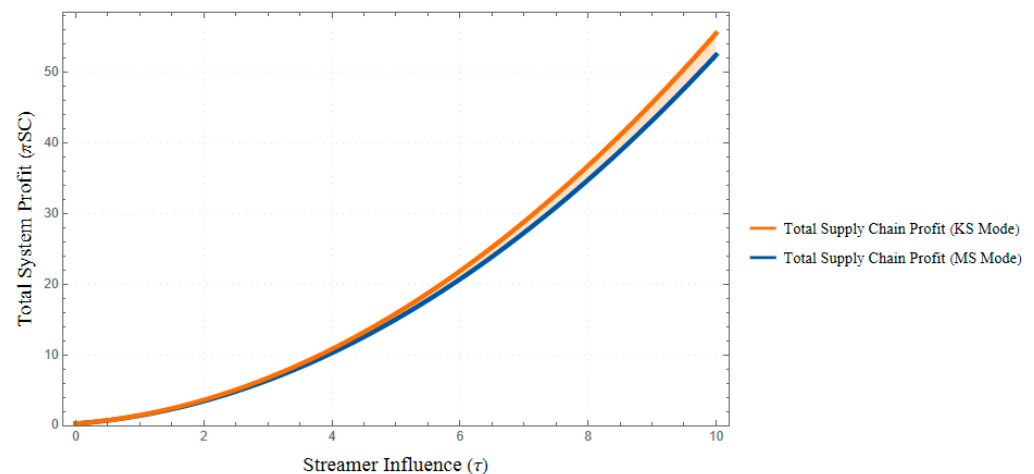


Figure 7. Comparison of total supply chain profit and efficiency surplus between KS and MS modes.

This “efficiency surplus” forms the basis for cooperation in the supply chain. Since the KS model creates a higher total value ($\Pi_{SC}^{KS} > \Pi_{SC}^{MS}$), the conflict is not a zero-sum game. Because the “pie” is larger, the brand, which is the main beneficiary, has the economic ability to share this part of the surplus with the streamer (for example, by increasing the commission or providing subsidies). As long as the shared part can cover the profit gap of the streamer, the income of both sides in KS mode will be better than that in MS mode. Therefore, the KS model is not only the preference of the brand but also represents the best result of the ecosystem, provided that the brand can use this surplus to align the incentives of all parties.

Under the premise of establishing the overall efficiency of the system, we assume that the redistribution of the surplus can meet the participation constraints of the streamer. Therefore, the key determinant of model adoption is the profitability of the brand. In the next section, we will explore the economic boundaries from the perspective of the brand to determine when it is of strategic significance to initiate the KS model.

6.3. Strategic Mode Selection: Economic Boundaries and Decision Maps

Though we can conclude from the analysis in Section 6.2 that the KS mode provides the greater return for the brand in general, we need an economic framework that enables us to identify any exceptions to this. This section isolates the interaction between the streamer influence (τ) and the commission rate (η) and is designed to map out the precise boundaries at which the brand should strategically switch between KS and MS modes.

In the graph presented in Figure 8a, we can see an indication of brand preference based on the quantified profit difference ($\Delta\pi_b = \pi_b^{KS} - \pi_b^{MS}$) between the two different market type models (KS vs MS). In the graph, profit differences have consistently shown a strong preference for the KS model, where as long as the commission rates continue to be in the normal commercial range (e.g., $\eta \leq 0.6$), the profit difference is positive, and the growth rate of profit differences increases dramatically as the influence of streamers increases. The data support the position that for the brand, the amount of profit received by adopting the KS mode will greatly outweigh the profit received by adopting the MS mode. The primary scenario where the brand would be well served by switching to the MS mode is if the streamer’s commission were to reach a level (e.g., $\eta > 0.8$) that would cause the brand’s profits to drop drastically. However, this would indicate that the streamer is taking advantage of the brand to capture virtually all of the surplus from the supply chain, a scenario neither likely to last long nor be accepted in a real-world commercial negotiation.

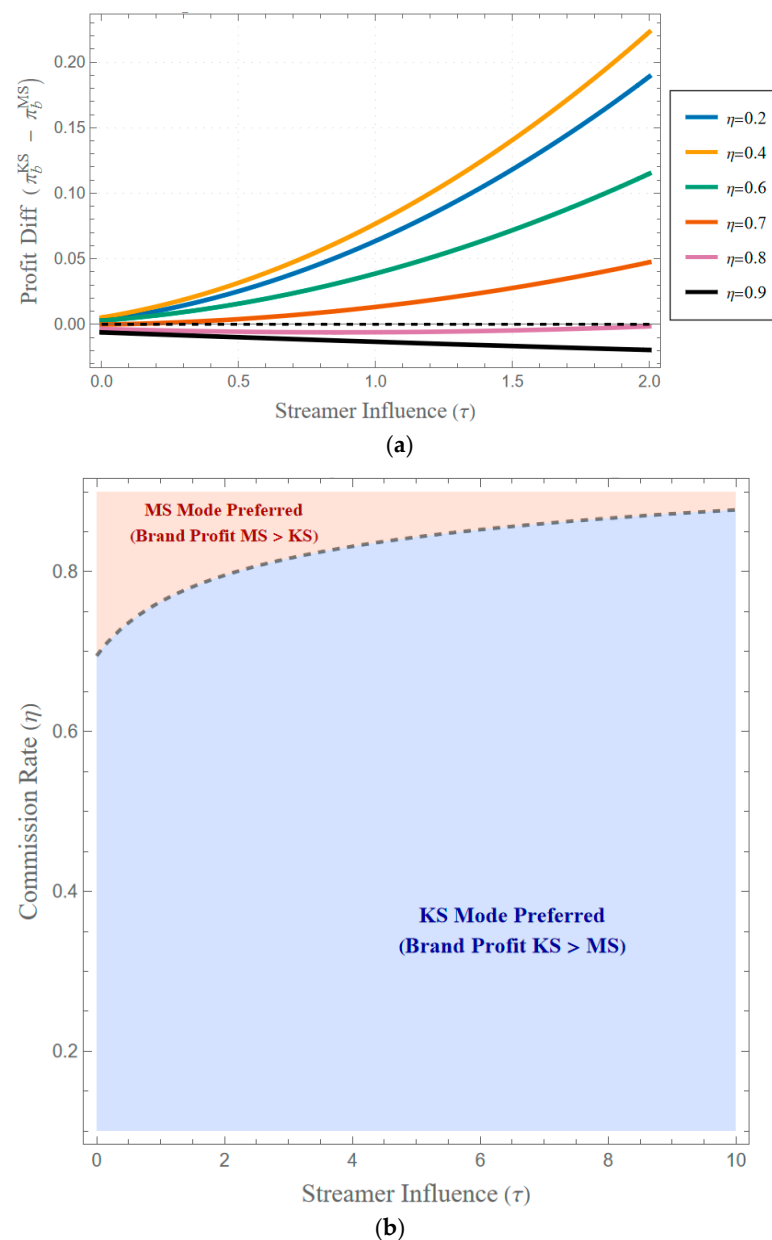


Figure 8. (a) Impact of commission rate (η) on the brand profit difference. (b) Strategic mode selection map for the brand.

The dominance that the KS mode exhibits was verified by the strategic selection map illustrated in Figure 8b, which shows the equilibrium boundary between a brand's preferred modes—each zone (decision area) is distinct from the other, with little overlap, and when comparing the areas of the two zones, there is an important takeaway. The KS preference zone (lower right) occupies the vast majority of the space available for all possible combinations of parameters, while the MS preference zone (upper left) is largely confined to theoretical edge cases where the commission required by the streamers would be excessive. Therefore, the implications of this analysis are as follows. The KS mode provides maximum profit for the brand. Consequently, partnering with streamers using the KS mode is a dominant strategy for the brand.

6.4. Strategic Synthesis: Consensus on Scale and Conflict on Structure

From the synthesis of the numeric analysis, two key takeaways have been distilled about streamer influence and power structure.

On the one hand, the analysis indicates that streamer influence has the capability to create value for both the brand and the streamer. It is apparent that regardless of the type of power structure utilized, streamer influence serves as the main driver of value; thus, it is in the strategic interests of both the brand and the streamer to maximize the level of influence generated through partner selection and audience accumulation.

On the other hand, the parties' choices of power structure differ greatly. The KS mode is the optimal option for brands, as it yields the highest profit when partnered with high-influence streamers. The MS mode provides streamers with the highest profit, producing better returns than the KS mode at the same level of influence. However, our system efficiency analysis confirms that this conflict is not a zero-sum game. Since the KS mode can generate a higher total surplus, preference differences are essentially a matter of coordination rather than a fundamental economic stalemate, suggesting that the KS mode remains the most stable and balanced choice for the ecosystem.

6.5. Discussion of the Numerical Results

Based on the numerical analysis, this study highlights three key insights regarding the operational mechanisms of the live-streaming supply chain.

In particular, with respect to streamer influence and consumer sensitivity, the results indicate that streamer influence is a significant determinant of overall supply chain success, a finding consistent with recent studies on the impact of streamer characteristics and popularity on sales performance [57–59]. In both KS and MS modes, there is a direct positive relationship between the streamer's increased influence, which is expressed through a greater total selling effort, increased paid traffic and retail price, and increased advertising spend. Streamers who have high sensitivity to non-price factors (γ) will be motivated to increase their marketing expenditures, which will further incentivize streamers to increase their marketing investment. Therefore, the sustainability of the actual economic size of the live-streaming model is closely connected to how much continued growth occurs with respect to streamers' personal influence and consumer engagement.

In addition, we have determined that there is a significant constraint on the streamer-led (KS) mode because of its operation. The KS mode is considered a high-return mode of operation but is also susceptible to high operational costs (C_1, C_2), consistent with theoretical findings that the efficiency of marketing efforts fundamentally constrains optimal pricing and profitability [60]. When the cost coefficients increase, the streamer will decrease marketing inputs, which requires the brand to lower prices to maintain equilibrium. Thus, it is clear that the operational scale of the KS mode is limited by cost efficiency.

Ultimately, the analysis of strategic mode selection shows that there is a clear choice amongst brands. The KS mode performs better than the MS mode in most commercial applications since the revenue generated from higher sales volumes exceeds the cost of commissions incurred. While prior research suggests that agency and self-implementing frameworks in live-streaming may yield indifferent performance outcomes [61], our analysis clarifies that the KS mode dominates by generating a structural "Efficiency Surplus" at the aggregate level. Therefore, the KS mode is the optimal strategy for the brand to create sustainable partnerships and maximize overall supply chain efficiency.

7. Conclusion and Managerial Implications

This study develops a game theory framework to analyze and model the ways that live-streaming supply chains operate and how the brand reaches equilibrium points. The goal was to develop a comparative assessment of the KS mode and MS mode. The decision models incorporated streamer influence, consumer sensitivities, and operational decisions; we conclude with the following principal findings of our research.

7.1. Main Research Conclusions

This paper provides the first major theoretical contribution that explains how streamers influence the operational strategy of brands. Our analysis shows that there is a direct positive relationship between streamer influence and the equilibrium decisions of the brand and the streamer for each of the power structures provided in Proposition 3. More specifically, as streamer influence increases, the streamer will increase both their level of selling effort and their volume of paid traffic investments. Likewise, in both KS and MS modes, the brand will increase the direct selling price as a result of increased streamer influence. Therefore, this suggests that, regardless of the brand's leadership structure, greater streamer influence will ultimately lead both the brand and the streamer to increase their marketing investments and prices simultaneously.

We evaluate the interaction between market factors. The second consideration is the impact of consumer sensitivity to the streamer's non-price attributes on the optimal decisions in the KS mode. Proposition 4 shows that an increase in consumer sensitivity (γ) has a positive effect on the KS mode optimal decisions of the supplier and streamer. A rise in consumer sensitivity increases the streamer's selling effort and the volume of paid traffic. The optimal retail prices will likely rise due to this consumer sensitivity. Thus, the best strategy for both the brand and streamer in a high-sensitivity market is to engage in larger amounts of marketing efforts.

In addition, we analyze how changes in an organization's cost structure affect the KS mode's sensitivity to those changes. Proposition 5 indicates that the KS mode is negatively sensitive to an organization's cost coefficients (C_1, C_2). This implies that when a company raises its operating costs, the optimal decision for the streamer is to reduce the input (effort/traffic). This, in effect, means that the KS mode for the organization will require lower direct selling prices from the brand due to the fact that it has fewer viable operating opportunities. So, as a result of increased operating costs, equilibrium levels of KS modes will be limited and hence will restrict the scale of their operation.

In addition to our previous theoretical review of strategic mode selection, this research also provides numerical support for the economic rationality of a brand's decision-making process and the corresponding theoretical findings. We use numerical maps to show that the KS strategy is predominantly preferred by the brand as an effective strategy. With respect to comparative brand profitability, the brand is observed to generate greater levels of profit from the KS mode compared to that associated with the MS mode because the revenue generated by increased volume sales is more than adequate to pay for the associated commissions. Therefore, brands should focus their efforts on developing partnerships with top-tier streamers in order to maximize their operational efficiency. Additionally, our study shows that there is an "efficiency surplus" in the KS mode at the overall level; therefore, the structural conflict can be resolved through profit redistribution.

7.2. Implications for Management

Based on our findings, the recommendations outlined below identify ways to optimize the effectiveness of partnerships with top-tier streamers. The analysis indicates that brands partnering with top-tier streamers will experience a much higher economic return than they would experience with ordinary streamers. Therefore, the recommended first step for brands is to identify and secure relationships with top-tier streamers. In regard to the type of partnership, the analysis demonstrated clearly that the KS mode offered greater economic benefits than the MS mode. As explained in Proposition 3, while the KS mode would require surrendering some degree of control over channels, the most significant benefit associated with a KS mode is the potential for a substantial "Positive Spillover Effect" since the top-tier streamer has such a substantial impact on total market demand, which

can result in the ability to increase direct selling price by brands without decreasing the volume sold. Therefore, rather than pursuing absolute channel leadership, it is suggested that brands move their efforts from developing absolute leadership to developing brands' revenues through streamer influence. In closing, our analysis suggests that the KS mode may represent an optimal method for capitalizing on the responsiveness of the fan economy.

Streamers' most important priorities should be influencing growth and cost-efficiency. According to theoretical analysis, the most critical factor for maximizing the absolute returns of a streamer is increasing their personal level of influence. It is recommended that streamers should continuously invest in their personal growth in order to create a large, loyal, and profitable fan base over time. Furthermore, if streamers assume the leadership role (KS mode) in order to support the brand, they need to be aware of their sensitivity to operational costs. The KS mode requires a significant amount of selling effort and traffic investment; as a result, streamers should prioritize cost control. In addition, in order for streamers to maintain a high-input strategy, they should negotiate higher commission rates or propose paying a fixed fee for the live-streaming in order to share the system-wide efficiency surplus created by the KS mode.

The findings indicate that for both the overall live-streaming industry and platform operators, one of the key takeaways is to reduce operational friction. Industry leaders should identify influential streamers as strategic assets that create value for the entire ecosystem. Industry stakeholders need to move away from simply distributing passive traffic and instead begin incubating mid-tier streamers and assisting them in building up the level of influence needed for success. In addition to this, platform operators need to address the constraints of the KS mode due to operational costs, as referenced in Proposition 5, so that cost shocks do not impact the ability of the ecosystem to support streamers at scale. By developing and implementing efficient data access tools and subsidizing traffic acquisition through innovative mechanisms, an ecosystem that operates at a low-friction level will be able to achieve the high-input, high-return equilibrium necessary to support the fan economy.

8. Limitations and Future Research

The assumptions made in this research limit the external validity of the findings and could be useful for further research. One assumption is that the model structure is single-brand and single-streamer to capture the vertical strategic interdependence of firms. In comparison to studies on platform ecosystems [62], the current study places no emphasis on multi-streamer competition or traffic rules related to platforms. Future studies can connect the current findings to a competitive setting to evaluate the overall system-wide trade-off of traffic allocation. Another assumption is based on the use of a deterministic demand function with full information, meaning that the uncertainty and asymmetry of information associated with demand while being hosted through live-streaming will not be captured [63,64]. Future research utilizing stochastic models of demand could examine the effect of influence on the risk of inventory decisions [65]. In addition, our outcomes concerning how sensitive consumers are to mechanisms are based on theoretical equilibrium reasoning. Future research can utilize empirical methods for estimating and testing hypotheses to confirm the behavioral assumptions we made about consumers' behavior. Furthermore, we have established a single-period static game as our model approach; using a multiple-period dynamic model would better reflect repeated interactions among consumers, the long-term build-up of influence from streamers, and the impact of reputations on the developing marketplace for live-streaming commerce.

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Appendix A

Appendix A.1. Proof of Proposition 1

Proof. We employ backward induction to solve for the Subgame Perfect Nash Equilibrium in the streamer-led top-tier (KS) mode. The game sequence is as follows: first, the streamer (leader) decides the selling effort θ and paid traffic volume δ ; subsequently, observing the streamer's decisions, the brand (follower) sets the direct retail price P_d .

Step 1: The Brand's Reaction Function (Stage 2)

Given the streamer's decisions (θ, δ) and the price linkage $P_s = (1 - \lambda)P_d$, we substitute Equations (5) and (6) into the brand's profit function Equation (7). The brand maximizes its profit with respect to p_d . The first-order condition (FOC) is given by:

$$\frac{\partial \pi_b^{KS}}{\partial P_d} = 0$$

Since the demand functions are linear, π_b^{KS} is strictly concave with respect to P_d . Solving the FOC yields the brand's best response function, denoted as $P_d(\theta, \delta)$.

Step 2: The Streamer's Optimal Decisions (Stage 1)

Anticipating the brand's reaction, the streamer maximizes π_s^{KS} (Equation (8)) by incorporating the reaction function $P_d(\theta, \delta)$. The decision problem becomes:

$$\max_{\theta, \delta} \pi_s^{KS}(P_d(\theta, \delta), \theta, \delta)$$

We take the partial derivatives with respect to θ and δ :

$$\frac{\partial \pi_s^{KS}}{\partial \theta} = 0, \quad \frac{\partial \pi_s^{KS}}{\partial \delta} = 0$$

Provided that the Hessian matrix of the streamer's profit function is negative definite (ensuring joint concavity), the solution to this system of simultaneous equations yields the optimal selling effort θ^{KS*} and paid traffic volume δ^{KS*} .

Step 3: Equilibrium Results

Substituting the optimal θ^{KS*} and δ^{KS*} back into the brand's reaction function $P_d(\theta, \delta)$ yields the equilibrium price P_d^{KS*} . The explicit expressions for θ^{KS*} (Equation (9)), δ^{KS*} (Equation (10)), and P_d^{KS*} (Equation (11)) are obtained through standard algebraic simplification.

This completes the proof of Proposition 1. $\square$

Appendix A.2. Proof of Proposition 2

Proof. Similar to the proof of Proposition 1, we employ backward induction to solve for the equilibrium. However, the sequence of moves is reversed in the ordinary (MS) mode. The brand (leader) first sets the retail price p_d , and, subsequently, the streamer (follower) determines the selling effort θ and paid traffic volume δ .

Step 1: The Streamer's Reaction (Stage 2)

Taking the brand's price P_d as given, the streamer maximizes π_s^{MS} (Equation (14)). Provided that the Hessian matrix of the streamer's profit function is negative definite (ensuring joint concavity), the optimal response functions $\theta(P_d)$ and $\delta(P_d)$ are uniquely determined by the first-order conditions:

$$\frac{\partial \pi_s^{MS}}{\partial \theta} = 0, \quad \frac{\partial \pi_s^{MS}}{\partial \delta} = 0$$

Step 2: The Brand's Optimization (Stage 1)

The brand anticipates these reactions and maximizes its profit π_b^{MS} (Equation (15)) by solving:

$$\max_{P_d} \pi_b^{MS}(P_d, \theta(P_d), \delta(P_d))$$

Solving the condition $\frac{\partial \pi_b^{MS}}{\partial P_d} = 0$ yields the equilibrium price P_d^{MS*} (Equation (18)). Substituting this into the streamer's reaction functions yields the equilibrium inputs θ^{MS*} (Equation (16)) and δ^{MS*} (Equation (17)).

This completes the proof of Proposition 2. $\square$

Appendix A.3. Proof of Proposition 3

Proof. Based on the equilibrium solutions derived in Section 4, we examine the sensitivity of the equilibrium decisions to streamer influence.

(i) For the KS Mode:

Taking the first-order partial derivatives of the optimal solutions in Equations (9)–(11) with respect to τ_H , it is straightforward to verify that:

$$\frac{\partial \theta^{KS*}}{\partial \tau_H} > 0, \quad \frac{\partial \delta^{KS*}}{\partial \tau_H} > 0, \quad \frac{\partial P_d^{KS*}}{\partial \tau_H} > 0$$

(ii) For the Ordinary (MS) Mode:

Similarly, taking the first-order partial derivatives of the optimal solutions in Equations (16)–(18) with respect to τ_L , it is straightforward to verify that:

$$\frac{\partial \theta^{MS*}}{\partial \tau_L} > 0, \quad \frac{\partial \delta^{MS*}}{\partial \tau_L} > 0, \quad \frac{\partial P_d^{MS*}}{\partial \tau_L} > 0$$

This completes the proof of Proposition 3. $\square$

Appendix A.4. Proof of Proposition 4

Proof. We examine the impact of consumer sensitivity (γ) on the equilibrium decisions in the KS mode. Taking the first-order partial derivatives of the optimal solutions in Equations (9)–(11) with respect to γ , it is straightforward to verify that:

$$\frac{\partial \theta^{KS*}}{\partial \gamma} > 0, \quad \frac{\partial \delta^{KS*}}{\partial \gamma} > 0, \quad \frac{\partial P_d^{KS*}}{\partial \gamma} > 0$$

This completes the proof of Proposition 4. $\square$

Appendix A.5. Proof of Proposition 5

Proof. We investigate the sensitivity of the top-tier (KS) equilibrium decisions to the operational cost coefficients (C_1 for selling effort and C_2 for paid traffic volume).

(i) Sensitivity to Selling Effort Cost (C_1):

Taking the first-order partial derivatives of the optimal solutions in Equations (9)–(11) with respect to C_1 , it is straightforward to verify that:

$$\frac{\partial \theta^{KS*}}{\partial C_1} < 0, \quad \frac{\partial \delta^{KS*}}{\partial C_1} < 0, \quad \frac{\partial P_d^{KS*}}{\partial C_1} < 0$$

(ii) Sensitivity to Paid Traffic Volume Cost (C_2):

Similarly, taking the derivatives with respect to C_2 , it is straightforward to verify that:

$$\frac{\partial \theta^{KS*}}{\partial C_2} < 0, \quad \frac{\partial \delta^{KS*}}{\partial C_2} < 0, \quad \frac{\partial P_d^{KS*}}{\partial C_2} < 0$$

This completes the proof of Proposition 5. $\square$

References

- Lu, B.; Chen, Z. Live streaming commerce and consumers' purchase intention: An uncertainty reduction perspective. *Inf. Manag.* **2021**, *58*, 103509. [\[CrossRef\]](#)
- Zhang, H.; Sui, R.; Zha, X. The key opinion leader introduction and pricing strategy for live streaming e-commerce platforms considering the impact of network effects. *J. Retail. Consum. Serv.* **2025**, *82*, 104077. [\[CrossRef\]](#)
- Lin, W.; Cai, Y.; Su, Y.; Lin, Q.; Lai, Q. Influence of key opinion leader on the brand advocacy of agricultural product: Taking Taobao live streaming as an example. *Curr. Psychol.* **2025**, *44*, 9390–9406. [\[CrossRef\]](#)
- Yang, R.; Xu, C.; Lyu, S. Impact of pricing power and network externality in a dual-channel live-streaming supply chain. *Electron. Commer. Res.* **2025**. [\[CrossRef\]](#)
- Li, T.; Xu, S.; Tan, Q.; Teng, W. Livestream Scheme Selection in the E-Commerce Supply Chain: Under Agency and Resale Sales Modes. *Systems* **2025**, *13*, 397. [\[CrossRef\]](#)
- Xu, S.; Tang, H.; Lin, Z.; Lu, J. Pricing and sales-effort analysis of dual-channel supply chain with channel preference, cross-channel return and free riding behavior based on revenue-sharing contract. *Int. J. Prod. Econ.* **2022**, *249*, 108506. [\[CrossRef\]](#)
- Liu, W.; Cao, X.; Niu, X.; Fang, X.; Choi, T.-M. Supply chain strategies in the presence of livestream e-commerce: Channel leadership and low-carbon promotion. *Ann. Oper. Res.* **2023**. [\[CrossRef\]](#)
- Zhang, Y.; Xu, Q. Power structures unleashed: Driving product and live content innovation in live streaming commerce. *Electron. Commer. Res.* **2026**, *26*, 677–704. [\[CrossRef\]](#)
- Bai, S.; Xu, Y.; He, H.; Yu, D. Under the context of competition between platform sales and live streaming sales, who has the pricing power of products? *Humanit. Soc. Sci. Commun.* **2024**, *11*, 1168. [\[CrossRef\]](#)
- Zhu, X.; Zhu, H.; Guo, Y.; Ding, L. Live streaming e-commerce supply chain decisions considering dominant streamer under agency selling and reselling formats. *Electron. Commer. Res.* **2025**, *25*, 1173–1198. [\[CrossRef\]](#)
- Song, J.; He, Y.; Duan, Y. Loss leader strategy in the live streaming considering cross-product and cross-channel spillover effects. *Int. J. Prod. Econ.* **2025**, *294*, 109803. [\[CrossRef\]](#)
- Zhang, W.; Liu, C.; Ming, L.; Cheng, Y. The Sales Impacts of Traffic Acquisition Promotion in Live-Streaming Commerce. *Prod. Oper. Manag.* **2025**, *34*, 3830–3846. [\[CrossRef\]](#)
- Xia, L.; Zhang, M.; Wang, J.; Hou, P. Platform traffic support strategies under dual live-streaming channels. *Transp. Res. Part E Logist. Transp. Rev.* **2025**, *203*, 104349. [\[CrossRef\]](#)
- Addo, P.C.; Fang, J.; Asare, A.O.; Kulbo, N.B. Customer engagement and purchase intention in live-streaming digital marketing platforms. *Serv. Ind. J.* **2021**, *41*, 767–786. [\[CrossRef\]](#)
- Guo, Y.; Zhang, K.; Wang, C. Way to success: Understanding top streamer's popularity and influence from the perspective of source characteristics. *J. Retail. Consum. Serv.* **2022**, *64*, 102786. [\[CrossRef\]](#)

16. Zhang, X.; Zhang, G.; Sun, H.; Shi, C.; Zhang, G. Operational decisions of live-streaming platform supply chain based on control power: Considering the dual preferences of consumers. *Prod. Plan. Control* **2023**, 1–30. [\[CrossRef\]](#)
17. Xiao, Y.; Yu, J.; Zhou, S.X. Commit on Effort or Sales? Value of Commitment in Live-streaming E-commerce. *Prod. Oper. Manag.* **2024**, 33, 2241–2258. [\[CrossRef\]](#)
18. Li, H.; Lu, J. The Ineffectiveness of ‘Volume Guarantee’ Mode in Live-Streaming: A Nash Bargaining Analysis with Social Network Effects and Traffic Costs. *J. Theor. Appl. Electron. Commer. Res.* **2025**, 20, 314. [\[CrossRef\]](#)
19. Shang, Q.; Ma, H.; Wang, C.; Gao, L. Effects of Background Fitting of e-Commerce Live Streaming on Consumers’ Purchase Intentions: A Cognitive-Affective Perspective. *Psychol. Res. Behav. Manag.* **2023**, 16, 149–168. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Duong, N.T.; Lin, H.-H.; Wu, T.-L.; Wang, Y.-S. Understanding Consumer Trust Dynamics and Purchase Intentions in a Multichannel Live Streaming E-Commerce Context: A Trust Transfer Perspective. *Int. J. Hum.–Comput. Interact.* **2025**, 41, 9123–9136. [\[CrossRef\]](#)
21. Fan, X.; Zhang, L. Social E-commerce Operations: Is it wise to adopt short video and live-streaming together? *Omega* **2026**, 138, 103440. [\[CrossRef\]](#)
22. Chen, H.; Dou, Y.; Xiao, Y. Understanding the role of live streamers in live-streaming e-commerce. *Electron. Commer. Res. Appl.* **2023**, 59, 101266. [\[CrossRef\]](#)
23. Gao, W.; Jiang, N.; Guo, Q. How cool virtual streamer influences customer in live-streaming commerce? An explanation of stereotype content model. *J. Retail. Consum. Serv.* **2025**, 82, 104139. [\[CrossRef\]](#)
24. Liu, S.; Xu, X.; Cheng, T.C.E. Equilibrium analysis of live-streaming e-commerce supply chain in the AI era. *Int. J. Prod. Res.* **2025**, 1–19. [\[CrossRef\]](#)
25. Wan, Q.; Chen, J.; Yu, C.; Lu, M.; Liu, D. Optimal marketing strategies for live streaming rooms in livestream e-commerce. *Electron. Commer. Res.* **2025**, 25, 4655–4688. [\[CrossRef\]](#)
26. Xin, B.; Hao, Y.; Xie, L. Strategic product showcasing mode of E-commerce live streaming. *J. Retail. Consum. Serv.* **2023**, 73, 103360. [\[CrossRef\]](#)
27. Ji, G.; Fu, T.; Li, S. Optimal selling format considering price discount strategy in live-streaming commerce. *Eur. J. Oper. Res.* **2023**, 309, 529–544. [\[CrossRef\]](#)
28. Li, K.; Yao, S.; Li, Y.; Tang, F.; Wang, Z. Deliberate shortage in live-streaming commerce. *Omega* **2025**, 131, 103201. [\[CrossRef\]](#)
29. Li, M.; Mizuno, S. Dynamic pricing and inventory management of a dual-channel supply chain under different power structures. *Eur. J. Oper. Res.* **2022**, 303, 273–285. [\[CrossRef\]](#)
30. Hu, X.; Cai, J.; Yue, X. Power structure preferences in a dual-channel supply chain: Demand information symmetry vs. asymmetry. *Eur. J. Oper. Res.* **2024**, 314, 920–934. [\[CrossRef\]](#)
31. Wu, H.; Li, G.; Liu, M.; Zhang, M. Launching big data-driven credit payment services? Role of power structure in a dual-channel supply chain. *Ann. Oper. Res.* **2025**, 348, 29–53. [\[CrossRef\]](#)
32. Wang, S.; Wu, J.; Chiclana, F.; Sun, Q.; Herrera-Viedma, E. Two-Stage Feedback Mechanism With Different Power Structures for Consensus in Large-Scale Group Decision Making. *IEEE Trans. Fuzzy Syst.* **2022**, 30, 4177–4189. [\[CrossRef\]](#)
33. Xiao, Y.; Niu, W.; Zhang, L.; Xue, W. Store brand introduction in a dual-channel supply chain: The roles of quality differentiation and power structure. *Omega* **2023**, 116, 102802. [\[CrossRef\]](#)
34. Zhang, G.; Zhao, S.; Yang, Y.; Li, C. Information Misreporting Behavior and Optimal Pricing Strategy in Dual-Channel Supply Chain Under Different Dominant Power Structures. *Mathematics* **2025**, 13, 3863. [\[CrossRef\]](#)
35. Yuan, M.; Qiu, R.; Sun, M.; Shao, S.; Fan, Z.-P.; Xu, H. Blockchain implementation decisions in a dual-channel supply chain under different market power structures. *Int. J. Prod. Res.* **2025**, 63, 5238–5262. [\[CrossRef\]](#)
36. Tao, F.; Wang, Y.-Y.; Zhu, S.-H. Impact of blockchain technology on the optimal pricing and quality decisions of platform supply chains. *Int. J. Prod. Res.* **2023**, 61, 3670–3684. [\[CrossRef\]](#)
37. Zhao, N.; Wang, J.; Pan, Y.; Wang, Q.; Min, J. Joint encroachment and low-carbon propaganda decisions in a platform supply chain under cap-and-trade regulations. *Int. J. Prod. Res.* **2025**, 63, 8320–8346. [\[CrossRef\]](#)
38. Gu, Z.; Zhao, X.; Wu, D.J. A Model of Shoppertainment Live Streaming. *Manag. Sci.* **2025**, 71, 6816–6835. [\[CrossRef\]](#)
39. Lv, X.; Zhang, R.; Su, Y.; Yang, Y. Exploring how live streaming affects immediate buying behavior and continuous watching intention: A multigroup analysis. *J. Travel Tour. Mark.* **2022**, 39, 109–135. [\[CrossRef\]](#)
40. Feng, X.; Rong, Y.; Tian, X.; Wang, M.; Yao, Y. When Persuasion Is Too Persuasive: An Empirical Analysis of Product Returns in Livestream e-Commerce. *Prod. Oper. Manag.* **2025**, 34, 3978–3997. [\[CrossRef\]](#)
41. Wang, S.; Esperança, J.P.; Wu, Q. Effects of Live Streaming Proneness, Engagement and Intelligent Recommendation on Users’ Purchase Intention in Short Video Community: Take TikTok (DouYin) Online Courses as an Example. *Int. J. Hum.–Comput. Interact.* **2023**, 39, 3071–3083. [\[CrossRef\]](#)
42. Zhao, K.; Lu, Y.; Hu, Y.; Hong, Y. Direct and Indirect Spillovers from Content Providers’ Switching: Evidence from Online Livestreaming. *Inf. Syst. Res.* **2023**, 34, 847–866. [\[CrossRef\]](#)

43. Zheng, R.; Li, Z.; Na, S. How customer engagement in the live-streaming affects purchase intention and customer acquisition, E-tailer's perspective. *J. Retail. Consum. Serv.* **2022**, *68*, 103015. [\[CrossRef\]](#)
44. Yang, X.; Gou, Q.; Wang, X.; Zhang, J. Does bonus motivate streamers to perform better? An analysis of compensation mechanisms for live streaming platforms. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *164*, 102758. [\[CrossRef\]](#)
45. Du, Z.; Fan, Z.-P.; Sun, F.; Liu, Y. Open the live streaming sales channel or not? Analysis of strategic decision for a manufacturer. *Ann. Oper. Res.* **2023**. [\[CrossRef\]](#)
46. Wang, H.; Pang, C.; Tang, H. Pricing and Carbon-Emission-Reduction Decisions under the BOPS Mode with Low-Carbon Preference from Customers. *Mathematics* **2023**, *11*, 2736. [\[CrossRef\]](#)
47. Yang, S.; Lai, I.K.W.; Tang, H. Pricing and Contract Coordination of BOPS Supply Chain Considering Product Return Risk. *Sustainability* **2022**, *14*, 5055. [\[CrossRef\]](#)
48. Ji, G.; Fu, T.; Choi, T.-M.; Kumar, A.; Tan, K.H. Price and Quality Strategy in Live Streaming E-Commerce With Consumers' Social Interaction and Celebrity Sales Agents. *IEEE Trans. Eng. Manag.* **2024**, *71*, 4063–4075. [\[CrossRef\]](#)
49. Xu, S.; Tang, H.; Huang, Y. Inventory competition and quality improvement decisions in dual-channel supply chains with data-driven marketing. *Comput. Ind. Eng.* **2023**, *183*, 109452. [\[CrossRef\]](#)
50. Xie, L.; Dai, L.; Hou, P.; Chen, P. Retailer Live Streaming Strategy in the Face of Manufacturer Encroachment Within Electronic Retailing. *IEEE Trans. Eng. Manag.* **2025**, *72*, 1668–1684. [\[CrossRef\]](#)
51. Xu, S.; Tang, H.; Lin, Z. Inventory and Ordering Decisions in Dual-Channel Supply Chains Involving Free Riding and Consumer Switching Behavior with Supply Chain Financing. *Complexity* **2021**, *2021*, 5530124. [\[CrossRef\]](#)
52. Luo, F.; Chen, S.; Xu, T.; Iqbal, M. Self-broadcasting or cooperating with an anchor? Strategy and dynamic system research on different sales modes in live commerce supply chain. *Electron. Commer. Res.* **2025**. [\[CrossRef\]](#)
53. He, P.; He, Y.; Ma, S. Strategic implications of consumer overconfidence for pricing and live-streaming in a platform service supply chain. *Int. J. Prod. Res.* **2025**, 1–21. [\[CrossRef\]](#)
54. Liang, Y.; Ren, X. Strategic KOL-platform marketing cooperation in livestream commerce. *Int. J. Prod. Res.* **2025**, *64*, 1183–1201. [\[CrossRef\]](#)
55. Sun, M.; Zhao, Q.; Peng, C.; Li, L. Should KOL live streaming be adopted? A target-oriented newsvendor analysis of supply chain performance. *Int. J. Prod. Res.* **2025**, 1–25. [\[CrossRef\]](#)
56. Zhao, C.; Li, Y.; Zhang, Y.; Li, L.; Wang, K. Honesty, Deception, or Collusion? Quality Information Disclosure in Live Streaming Commerce. *Manag. Decis. Econ.* **2026**, *47*, 309–332. [\[CrossRef\]](#)
57. Xu, X.; Zeng, Q.; Na, R.; Fan, W. Unveiling the influence of streamer characteristics on sales performance in live streaming commerce. *Electron. Commer. Res. Appl.* **2025**, *72*, 101510. [\[CrossRef\]](#)
58. Lu, B.; Li, G.; Ge, J. Effects of streamer effort and popularity on livestream retailing performance: A mixed-method study. *Electron. Commer. Res.* **2025**, *25*, 2553–2583. [\[CrossRef\]](#)
59. Yang, X.; Liu, Y.; Dong, J.; Li, S. Impact of streamers' characteristics on sales performance of search and experience products: Evidence from Douyin. *J. Retail. Consum. Serv.* **2023**, *70*, 103155. [\[CrossRef\]](#)
60. Karray, S.; Martín-Herrán, G. The effects of decision timing for pricing and marketing efforts in a supply chain with competing manufacturers. *Int. Trans. Oper. Res.* **2024**, *31*, 568–615. [\[CrossRef\]](#)
61. Ma, X.; Liu, S. Information disclosure strategies of live-streaming supply chains in the digi-economy era. *Manag. Decis. Econ.* **2024**, *45*, 5696–5713. [\[CrossRef\]](#)
62. Xue, J.; Liu, M.T. Investigating the live streaming sales from the perspective of the ecosystem: The structures, processes and value flow. *Asia Pac. J. Mark. Logist.* **2022**, *35*, 1157–1186. [\[CrossRef\]](#)
63. Zhang, H.; Feng, S.; Li, M. Contracting in live streaming e-commerce retailing under dual information asymmetry: The role of competition. *Int. Trans. Oper. Res.* **2025**, itor.70040. [\[CrossRef\]](#)
64. Lu, B.; Xu, X.; Li, Y.; Wang, J.-J. Logistics pricing strategy considering information uncertainty in live-streaming commerce. *Int. J. Prod. Res.* **2025**, 1–23. [\[CrossRef\]](#)
65. Du, Z.; Li, X.; Fan, Z.-P. Inventory and pricing decisions of brand owners and streamers under demand uncertainty. *Ind. Manag. Data Syst.* **2025**, *125*, 1052–1077. [\[CrossRef\]](#)

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